Understanding the Decline in Occupational Mobility *

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Abstract

The process of workers switching from occupation to occupation is a vital part of career development and self-discovery. Using publicly available U.S. survey data, we show that occupational switching rates have declined significantly over the past 25 years. This decline has been robust for each consecutive cohort and is more pronounced among younger than older workers. The decline may suggest that it is becoming more difficult and costly for workers to find better jobs, leaving people increasingly stuck in poorly matched and unfulfilling careers. Paradoxically, it could also mean that finding better jobs is becoming easier, since workers with good job matches are less likely to switch. This paper develops a dynamic discrete choice life-cycle model to separately identify and quantify how changes in switching costs and information over time contribute to the observed declines in occupation switching. We find that increased switching costs drive about 72% of the decline, while better information drives about 8%. The increases in switching costs have led to less productive occupational matches for workers and thus significant welfare losses.

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1 Introduction

The process of workers switching from occupation to occupation is a vital part of career development and self-discovery. Switching occupations allows workers to search for positions that best match their interests and abilities. Workers may switch occupations many times during the course of their career in order to find the most suitable position.[1] However, occupational switching rates have declined from 5.7% to 3.2% over the past 20 years.[2]

This decline raises concerns for policy makers. It could mean that the economy is becoming less flexible, potentially due to regulatory environment changes. This would imply that it is growing more difficult and costly to switch to better-matched occupations, leaving people increasingly stuck in poorly matched and unfulfilling careers. If the decline in switching rate is indeed associated with a less flexible economy, workers will be more mismatched and will adjust more slowly in the process of finding appropriate occupations.[3] An alternative explanation is that workers no longer need to switch occupations as their initial choices are better matches on average, reducing incentives for subsequent switches. So the drivers behind the decline in the occupational switching rate may be benign or even beneficial. Thus, the appropriate policy response to observed declines in switching and how these policies affect welfare depends critically on the explanation for the decline. To this end, a careful analysis and exploration of what's driving the decline in the switching rate is an important area of research.

In this paper, we first use data from the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP) to document the decline in the occupational switching rate, in line with the existing literature.[4] We find that the majority of this decline

[1] Over 40% of high school graduates transition between white and blue collar occupations more than once between the ages of 18 and 28. Many workers make occupation transitions within one year of entering the labor force, with the average time until the first occupation switch being roughly 1.5 years (Gorry, Gorry and Trachter (2014))

[2] Authors' calculations using SIPP from 1993 to 2013. The rates are calculated using a list of six broadly defined occupations (see data section for details). With more detailed occupation definitions, the switching rates are higher, but the decline remains. Details about the sample selection is introduced in the data section.

[3] Recent literature has identified job-to-job switching as an important indicator for labor market flexibility and fluidity. See, for example, Hyatt and Spletzer (2013) and Davis and Haltiwanger (2014)). Bowlus and Robin (2004) investigate worker's lifetime earnings through labor market transitions; Flinn (2002) has also shown that the high frequency of movements between labor market states leads to a more equitable distribution of lifetime welfare in the United States.

[4] For example, Moscarini and Thomsson (2007) documented the decline in the occupational switching rate using the CPS data. We primarily employ IPUMS CPS data (Flood et al. (2015)). Figure 1 shows the results using the IPUMS data. This decline in occupational switching rate remains when considering finely or coarsely defined occupation groups.

is not due to changes in worker demographics and industry composition. We then document that the decline in occupational switching rates over the past 20 years primarily affects young workers. In fact, the decline in the occupational switching rate for young workers was almost five times greater than the decline for older workers in percentage points.[5] Furthermore, we show that the decline in occupational switching rate has increasingly affected each of the successive cohorts over the past 20 years especially for the young.

These empirical facts suggest that changes in young workers' switching patterns contributed significantly to the observed aggregate decline in switching rates. Job mismatch is often greater among young workers relative to older workers because young workers have limited information about their match quality and need more time to learn about and discover their true abilities and interests (Gervais et al. (2016)). Furthermore, young workers are often more resource constrained than older, established workers. Thus, changes in young workers' information about their match quality, as well as the switching frictions they face, may play a significant role in explaining the observed decline in young workers', and therefore the aggregate, low switching rate. What may give workers more information about their match quality or the characteristics of a particular occupation? One possibility is the dramatic growth in information and communications technology (ICT) since the early to mid-1990s. ICT allows workers to quickly learn about skill requirements and job characteristics. It also improves education and self-knowledge, enabling workers to better estimate their likely performance in occupations before entering them. This idea is supported by empirical evidence. Faberman and Kudlyak (2016) show that workers are increasingly using online job search methods and that the job finding rate is higher for workers who have access to the Internet at home. In the Baccalaureate and Beyond Longitudinal Study by the National Center for Education Statistics, new college graduates were asked, 'Do you consider your current occupation part of your long-term career?' Of the students who graduated in 1993 and 2008, 54.5% and 84% respectively answered "strongly agree" or "somewhat agree". Furthermore, Molloy et al. (2016) show an increase in average starting wages for young workers aged 22-34 from the early 1990s to 2013. Hyatt and Spletzer (2016) show the median years of tenure has increased from 3.5 to 4.5 between 1990 and 2012. Since better match quality is often associated with higher starting wages and longer tenure, these empirical findings motivate a more careful analysis of how information and match quality play a role in worker career choices. Evidence of increases in switching costs is also significant. For example, Cairo (2013) shows that average employer training requirements have increased from 1983 to 2010.

[5] Author's calculation using the CPS three digit occupation code.

Gittleman, Klee and Kleiner (2015) and House (2015) show that occupational licensing has grown sharply over the past few decades, which, along with possible increases in the costs of retraining, may contribute to increases in switching costs. Using newly constructed data , Kleiner and Xu (2023) show that occupational licensing requirements have increased for all of the universally licensed occupations from the 1980s to 2016, and that this increase has significant negative effects on worker occupational switching rates.

To further test and examine these insights, we develop a dynamic discrete choice model featuring information frictions, learning about heterogeneous occupation-specific match quality, and occupational switching costs. Younger workers are unsure about their own occupation-specific abilities and preferences, so they switch between occupations while learning about their abilities in a Bayesian fashion. If information becomes more precise, young workers will know better about their match quality prior to entering the labor force and will quickly find their most suited occupation. In this case we will see young workers switching occupations less over time while older workers are not affected as much. If switching costs increase over time workers of all ages will similarly switch less frequently. Furthermore if switching costs differ with worker age it can lead to similar changes in that the decline in occupation switching rates are more prominent among young workers. This poses a challenge in identification, which we overcome using the wage gains associated with occupational switches. Intuitively, if information becomes more precise, occupational switchers on average would see lower wage gains associated with switching because they are correcting "smaller" errors in match quality. If switching costs increase, we would see occupational switchers experiencing higher wage gains on average since the gains from switching would have to sufficiently compensate the increased switching costs. These two factors, although driving occupational switching rates similarly, influence the gains from switching in opposing directions, enabling the separate identification of both factors.

This paper makes three contributions. First, we construct synthetic cohort using SIPP and establish a novel fact that the decline in occupational switching rate has increasingly affected each of the successive cohorts over the past 20 years. Second, using a dynamic discrete choice model we separately identify the effects of changes in information from changes in switching costs on occupational switching rates. We then estimate the model by fitting a transition path of parameters to the synthetic cohort data, and we assemble year-by-year cross sections of data using the simulated cohorts. This allow us to do exact comparison between the cross-sectional agents in the simulation to cross-sectional agents in the data, rather than simply assuming the economy is in steady states.[6] Lastly guilded by our model findings we use the Occupational Licensing Law Research Project (OLLRP) data and run policy experiments. We find that the two mechanisms, information and switching costs, both contribute significantly to the decline in occupational switching rate, and together they can account for up to 80% of the total decline. The improvements in initial information mainly affect the young, but the change in switching costs affects all workers. Therefore, in the aggregate, switching costs have a much bigger effect on the decline in occupational switching rates than initial information. Switching costs alone contribute up to 72% of the total decline. We show that the improvement in initial information increases workers' income and welfare, whereas the increase in switching costs has the opposite effect. Using compensating variation analysis, the model suggests that the total welfare change due to the two factors is much bigger than when solely considering workers' lifetime income. This is because the compensating value includes monetary as well as non-pecuniary utility compensation. The average welfare cost from increasing switching frictions for workers who enter the labor market between 1993 and 2013 is about 3% of workers' lifetime income, and some workers lose more than others. For example, the distribution of compensating values for workers who start to work in 2003 and also lose due to switching costs shows that the agent at 95th percentile of utility loss loses roughly 12% of lifetime income.

This paper proceeds as follows. In section 2, we use the CPS and SIPP to show the key features in the data. In section 3, we present the model and discuss the main driving forces behind the decline in occupational switching rates. We then show the quantitative analysis in sections 4 and 5, and describe the estimation results and experiments. Lastly, we conclude in section 6.

2 Data and Empirical Evidence

In this section, we document the decline in occupation mobility using two different data sets: the CPS and the SIPP. The CPS is an important source of official U.S. labor market statistics. It is also the primary source of data used by many researchers to study worker flows across occupations, industries and employers. The CPS has large nationally representative

[6] Assuming the economy in steady states is widely used in the literature and can simplify the computation process drastically. However, this assumption can not be simply applied here as we are comparing two cross-sections across 20 years span. Young agents in the first steady state period (for example, in 1995) progress in their life and enter the second steady state period (2005) as older agents, which conflict with the different steady state assumption. Further details of the calibration and simulation process is presented in Section 5.

monthly cross sectional samples, as well as a limited panel dimension.[7] Therefore it is useful for analyzing high-frequency labor market movements and changes in aggregate variables, though not as much for looking at changes in particular agents over a long period. We use the CPS primarily for constructing and documenting the aggregate empirical facts. Due to the limited nature of its panel dimension and wage information, we do not use it for the model estimation. The SIPP is a household-based survey designed as a continuous series of national panels. Each panel features a nationally representative sample interviewed over a multi-year period lasting approximately four years. Compared with other panel data surveys such as the Panel Study of Income Dynamics (PSID) and National Logitudinal Survey of Youth (NLSY), the SIPP has a relatively shorter panel, but much larger sample size ranging from approximately 14,000 to 52,000 interviewed households. This makes it suitable for aggregate analysis, and decreases worries about sampling error when measuring employment distributions across disaggregated cells, such as three-digit occupations (analysis which would be impossible with a smaller dataset such as the NLSY). Given the rich information about workers' work history, income, and demographics available in the SIPP, we use it as the primary data set for both the empirical evidence and the model estimation sections of this paper.

2.1 Declines in Occupational Mobility

We first explore the CPS monthly data from 1994 to 2016, using a similar cleaning process to Moscarini and Thomsson (2007).[8] Our primary sample for the CPS is working age (20-64) male workers who are employed between survey months 2 and 3.[9] Figure 1 shows that the monthly switching rate for this sample decreased consistently between 1994 and 2016, declining from about 3.5% to 2.2%.[10] To put this 40% decline in switching rate in context, consider that in 1994, there were about 3.9 million workers switching occupations every month, and this number decreased to 2.8 million in 2016. The graph shows that the number of switchers has been reduced by 1.1 millions even though over the past 20 years, employment

[7] Much of the literature on job and occupation mobility has used the CPS as a major source of evidence, including Fallick and Fleischman (2004), Nagypál (2008) and Moscarini and Vella (2008).

[8] Moscarini and Thomsson (2007) carefully analyze the CPS occupation and employment data in order to develop their method for dealing with suspicious records and measurement error. We follow their procedure in order to maintain comparability with the rest of the literature

[9] Results including both males and females are shown in Figure B.2. Overall, the switching rate decline is robust across various sample selection methods. See Appendix B for details.

[10] The occupation categories follows the occupational classification in Dorn (2009), and is defined at the 3-digit occupation code level. An investigation of job or employer switches reveals similar trends.

levels have gone up by 30 million. Moreover this decline is robust across different occupation classification methods. Using coarsely defined six occupation classification, the decline in switching rate remains. This result is shown in Figure B.1 in Appendix B.[11]

Many studies have also looked at labor market mobility and transition using the March CPS.[12] Using data on current occupation and questions about previous occupations, one can calculate an annual occupational switching rate that has declined from about 10% in 1994 to 8% in 2015. From its peak in 1995 to the zenith in 2010, this rate nearly halved, though it has recovered some since the end of the Great Recession.[13] This supports the evidence for a declining switching rate, however the switching rate measured by this method may not represent the true annual mobility. Kambourov and Manovskii (2013) argue that the annual switching rate obtained using the historical questions in the March CPS is closer to the three to four-monthly switching rate, which is about 6 times smaller than the annual switching rate they obtain from the PSID. However, though the level of annual switching rate may require more investigation, the fact that this rate has been declining over time remains.

The SIPP panel is our primary data source due to its large sample size and longer panel structure. The SIPP interviews households every four months with a short recall period (monthly). Because the SIPP has a short panel structure, each agent panel is not really suitable for long time series analysis, however a comparison across panels shows that the average four month switching rate has dropped from 5.65% to 3.24% between 1993 and 2013.[14] We examine the four month switching rate rather than one month rate because the SIPP suffers from seam bias: the tendency for estimates of change estimated across a "seam" between two consecutive surveys to exceed changes measured within a single interview. This result showing declines in the occupational switching rate is also robust for 3 digit occupation codes, 2 digits, and 1.[15] As further evidence, Hyatt and Spletzer (2013) use the Longitudinal Employer-Household Dynamics (LEHD) to confirm the decline of the job switching rate. Details about the SIPP sample selection can be found in the Appendix B.

[11] The six occupations are: 1. Managerial and Professional 2. Technical, Sales and Administration Support 3. Service Occupations 4. Farming, Forestry, and Fishing 5. Precision Production, Craft and Repair 6. Operators, Fabricators and Laborers.

[12] for example, Bowlus and Robin (2004) uses the matched March CPS to analyze lifetime inequality through a labor transition framework.

[13] https://www.stlouisfed.org/on-the-economy/2015/august/occupational-switching-occurring-less-often

[14] Author's calculation using 6 coarsely defined occupation groups

[15] Similar to above, the occupation categories follows the occupational classification in Dorn (2009)

2.2 Key Patterns of Occupational Switching

This subsection examines demographic and economic patterns in occupational mobility over the past 20 years.

It is well recognized that occupational mobility declines with age. This is shown clearly in Figure 2 using the CPS data that younger workers have been consistently switching occupations more often than older workers in the past two decades, and the magnitude of the decline in occupational switching rate over the past two decades for young workers is more prominent compared to the older workers. If younger workers tend to switch jobs or occupations more often than older workers, one may expect that an aging population will drive occupational mobility down. Similarly, gender, occupational composition and educational composition may also play a role in the decline of switching rates. In Figure 3, we show that the occupation switching rate declined for workers with all education backgrounds, though workers with bachelor degrees or higher have the lowest occupation switching rates, both now and in the past. If more workers today hold bachelor degree, these compositional shifts may contribute to the overall decline in occupational switching rates. Similarly in Figure 4 and 5, we see differences in the levels and decline in occupation switching rates by gender and broadly defined occupational groups. We further examine the occupational switching probabilities in a transition matrix for years 1992 to 1993 and for years 2012 to 2013, and we show the difference between the two transition matrices in Table 1 and D.1. Table 1 shows the results for 6 broadly defined occupations, and Table D.1 shows the results for more finely defined 17 occupation groups. Examining these two tables reveals very clear patterns: workers are increasingly likely to stay in their own occupation. This is true for both coarsely and finely defined occupation groups. The intuition comes from the fact that all diagonal terms in Table 1 and D.1 are above zero, while almost all off-diagonal terms are below zero. Furthermore, we see that workers are less likely to move to managerial and professional, and technical, sales and administration support professions, from other occupations, perhaps due to the more difficult entry barrier for these professions. To examine the potential composition effects of observable characteristics, we took a closer look at the data. Figure 6 illustrates an accounting decomposition of the switching rates by these different factors. When fixing the age, education, and race distributions at their early 90s level and allowing the group-specific switching rates to change over time as observed in the data, most of the decline remains, so changes in the distribution of these groups over time can only account for a very small fraction of the change in switching rates.[16] We further

[16]The age groups 20-24, 25-29, 30-34, ... 60-64. The education groups are: less or equal to high school,

show in Figure 7 the decomposition when holding the industry distribution and occupation distribution constant.[17] The result indicates that neither of these factors contribute much to the total occupational switching rate decline, and the change in switching behavior is a change in group-specific switching rates rather than a change in group composition such as aging baby boomers.[18] This result is in line with the literature on declining job mobility: for example, Hyatt (2015) uses LEHD data to show that firm size and age can't explain much of the decline. Similar to our own findings, they find that all the distributional effects they consider combined can explain at most 30% of the total decline of the job mobility, with the majority still remaining unexplained. Our focus in this paper is then to consider how much can information friction and switching costs account for the unexplained portion of this decline

A key feature in the data that we aim to capture and match using our model is that the occupational switching rate declined for all age groups but more prominently for young and new workers, illustrated in Figure 8. The top line in Figure 8 shows the occupational switching rate by age from 1992 to 1993 while the bottom line shows the occupational switching rate by age from 2012 to 2013.[19] Over the 20 years in question, the occupational switching rate dropped from about 14% to 7.5% for 20 year old workers, which is a 46% decline in switching. Older workers also saw a decrease in switching, but to a much lesser degree - the average switching rate for 60 year olds only dropped by 1.3 percentage points, a change from 2.8% to 1.5% over 20 years. The result holds for all occupation classifications and groupings, for example when using more finely defined 3 digit occupation groups. Younger workers are much less occupationally mobile than they used to be. Any attempt to explain

some college or associate degrees, greater or equal to bachelor degree. The race groups are white and none-white.

[17]The industry groups are: 1. Agriculture, Forestry and Fisheries 2. Mining 3. Construction 4. Manufacturing 5. Transportation, Communications, and Other Public Utilities 6. Wholesale Trade 7, Retail Trade 8 Finance, Insurance and Real Estate 9. Business and Repair Services 10. Personal Services 11. Entertainment and Recreation Services 12. Professional and Related Services 13. Public Administration. The occupation groups are: 1. Managerial and Professional 2. Technical sales and Administration Support 3. Service Occupations 4. Farming Forestry and Fishing 5. Precision Production, Craft and Repair 6 Operators Fabricators and Laborers

[18]For example, Figures 3, 4 and 5 show that occupational mobility decline appears in all gender, education and occupation groups.

[19]We compared these years in the empirical and model analysis since they bound the maximum period we can study using the SIPP while still keeping the survey questions and design comparable over time. The SIPP, starting in 2014, underwent major reforms and no longer resembles the same panel/wave structure as earlier SIPPs. Therefore, the newer SIPPs are unsuitable for our analysis as they are not comparable to the earlier data. The beginning period (1992) that we are looking at overlaps with a recession. Since people tend to switch less during the recession, this makes the decline of occupational switching rate we analyse a lower bound.

the decline in mobility must account for this fact. Our model thus reproduce this age-specific dynamics in switching rates. We also find that in the data the occupational switching rates declined for all occupation groups, but there are clear cross-occupation differences. While this paper focuses on average switching rates across all occupations, the approach can easily extends to allow for heterogeneous switching frictions and learning processes across occupations.

One potential issue with comparing cross sectional switching rates by age is that they don't directly reveal the data trend which connects the two – perhaps one of the two years was just abnormally high or low relative to every other year cross-section not pictured. However, the time series of the aggregate switching rate in the CPS suggests that this isn't the case. To strengthen the argument that the switching rate has been declining over time, we use all the data available from the SIPP panels from 1991 to 2013 to construct consecutive synthetic cohort-based occupational switching rates. For example, to construct the time series of switching rates for the cohort which entered the labor market in 1993, we calculate occupational switching rates for 20-year-olds in 1993, then 21 year-olds in 1994 and so on. For this cohort, we can calculate the switching rate all the way up to 40 year olds in 2013. Even though each SIPP panel only lasts 3 years, and the cohorts consist of different people, the samples are representative enough to use this method to construct a measure of actual cohort aggregate switching rates over time. Figure 10 shows the result of the synthetic cohort (partial) lifecycle occupational switching rates for some of the cohorts in the data.

The graph, from the left to right, plots the partial life cycle occupational switching rate age profiles for several cohorts (by birth year) between 1991 and 2013. The latest cohort entered the labor market in 2013, so we only see them once. Their switching rate is the dot on the left side of the figure. Moving to the right, the next cohort we show enters the labor market in 2008 (at age 20). Given the data, we observe them from age 20 to 25, so we can calculate the first 5 years of their cohort's switching rate age profile. Moving to some of the older cohorts provides more years of data. For example, we observe the 1973 cohort (20 years old in 1993) for 20 years in total, all the way until they are 40 years old in 2013. The very earliest cohort we see in this time frame are the workers who retire in 1992, so we only observe them once in 1991.

This synthetic cohort graph shows a novel fact: each subsequent cohort over the past 20 years has had a strictly lower switching rate age profile than the previous cohort, leading to a constant negative trend in overall switching rate. Furthermore, this graph also confirms the previous observation: the drop in the switching rate between cohorts is much larger for young workers than older workers.

3 Model

The empirical findings show that the occupational switching rate has declined for all age groups, especially for young workers. We also observe both common and heterogeneous changes in occupational switching. Guided by these empirical findings, we construct a dynamic discrete model of occupation choice with two key mechanisms that can drive changes in the occupational switching rate: changes in information technology such as pre-career education, and changes in occupational switching costs. As mentioned in the introduction, these two factors may both contribute to the decline of the overall switching rate. However, they have very different implications. Advances in information technology and improved education will increase young workers' information about their own abilities and the characteristics of different occupations or jobs before they enter the labor market, which tends to lead to better initial matches between workers and occupations, and lead to higher incomes and welfare. This would mean that workers have less incentive to switch occupations. At the same time, if switching rates are declining because retraining is more costly, or occupational licensing becomes stricter, then workers will be similarly less likely to switch, but worse off.

We model occupational choice as an optimal dynamic search process. The basic assumption is that agents use wages as a signal to learn about their occupation-specific ability or match quality. Self learning and discovery throughout their career drives workers to switch occupations, especially for the young who are relatively uncertain of their abilities or proclivities. There are many papers that have investigated the effect of learning on occupational switching. For example, Guvenen et al. (2015) propose that learning is an important aspect of a worker's experience in the labor market, and switching occupations is part of this process. Several recent papers, including Kennan and Walker (2011) and Kaplan and Schulhofer-Wohl (2012), have also looked at the effect of knowledge and learning on migration rates, finding that information plays an important role. Switching costs in our model can vary by age, time, and occupation-specific characteristics.

In this model, workers are endowed with an agent-occupation specific level of ability about which they are uncertain. In each period they choose the occupation which they believe can give them the highest discounted lifetime utility. The information available to workers prior to entering the labor force (referred to throughout as the education signal) gives workers their first clue about their own ability. Throughout their career, they learn about their occupation-specific ability by working in that occupation, using wages as a signal. When workers decide to switch, they face occupational switching costs which can differ across time, age, and occupational characteristics. The model is intended to describe the partial equilibrium response of labor supply to wages (which workers take as exogenous), switching costs and the information structure across occupations. Firm decisions certainly play a critical role in determining supply of vacancies across occupations, labor market characteristics and wages. While we do not model this directly, it can be partially captured by the occupational switching cost structure in the model, since workers take these costs into account when they move from occupation to occupation, and we allow these costs to evolve over time. A simple assumption here is that if a worker pays the applicable switching cost, they can become qualified to perform any occupation. This model can be viewed as a building block toward an equilibrium analysis of occupational choice and mobility.

3.1 Model setup

Environment

The economy consists of heterogeneous agents who live for T discrete periods, and differ in their match quality to different occupations. Individuals choose among J occupations: $j \in \{1, 2, ..., J\}$. When first entering the labor market, agents draw a permanent match quality for each occupation: $\nu^j \sim \mathbb{N}(0, \sigma_\nu)$, which can be thought of as a productivity term since it will enter into the wage. Individuals do not observe their true match quality; instead they base their occupational choices on their beliefs about their match quality for each occupation. While working in occupation j, agents receive wages w^j, which both enters into utility and acts as a signal of their match quality for occupation j. Individuals update their beliefs about their true match quality in a Bayesian fashion. Those who decide to leave their occupation (j) and switch to a different occupation (k) in the next period pay a switching cost conditional on their own state.

Preferences

Individuals are risk-neutral and choose a sequence of occupations to maximize their expected discounted lifetime utility:

$$\mathbb{E}\sum_{t=1}^{T}\beta^{t-1}\Big(u_t+\zeta_t\Big)$$

where u_t represents agent pecuniary utility and $u_t = w_t - \kappa_t$. w_t represents the wage the agent receives in period t, and κ_t represents the potential switching cost that agent pays in period t. ζ_t represents a non-pecuniary preference component of the utility. Both wages and switching costs depend on agents' state vector, including age, current occupation, beliefs and precision about the matching quality of each occupation. The preference component is occupation-specific. Specifically, ζ is a J-vector random variable that is assumed to be independently and identically distributed (i.i.d.) across occupations (1 to J) and across time periods, independent of the state vector.

The Recursive Problem

Given a vector of state variables x, which includes age, work history and beliefs over match quality, the period utility for an agent who chooses occupation j is:

$$u(x,j)+\zeta^j$$

where $u(x,j) = w(x,j) - \kappa(x,j)$. The agent's decision problem in recursive form is

$$W(x,\zeta)=\max_j\Big(u(x,j)+\zeta^j+\beta\sum_{x'}p(x'|x,j)\mathbb{E}_\zeta W(x',\zeta)\Big) \tag{1}$$

Here $p(x'|x,j)$ represents the transition probability from state x to state x' when occupation j is chosen, and $\mathbb{E}_\zeta$ denotes the expectation with respect to the distribution of the J-vector ζ with components ζ^j. Let $\rho(x,j)$ denote the probability of choosing occupation j given state vector x. We can re-write the value function as

$$W(x,\zeta)=\max_j(V(x,j)+\zeta^j)$$

where

$$\begin{aligned}V(x,j)=&u(x,j)+\beta\sum_{x'}p(x'|x,j)\mathbb{E}_\zeta W(x',\zeta)\\=&u(x,j)+\beta\sum_{x'}p(x'|x,j)\rho(x',j')V(x',j')\end{aligned}$$

We assume ζ^j is drawn from a type I extreme value distribution. In this case, following Rust(1987), the probability of choosing occupation j in state x is

$$\rho(x,j) = \frac{\exp(V(x,j))}{\sum_{k=1}^{J} \exp(V(x,k))}$$

This allows us to integrate out over the preference shock and greatly simplifies the solution to the worker's problem.[20]

Information and Wages

Recall that each agent has a J-vector ν of match quality terms: $\nu = (\nu^1, \nu^2, ..., \nu^J)$, one for each occupation, which is fixed over time. Individuals do not know these match qualities and must learn about them over time, making decisions which depend on these beliefs about matching quality, and their relative level of uncertainty. Prior to entering the labor force, each agent's belief about their vector of match qualities is equal to the true population distribution of quality: $\nu^j \sim \mathbb{N}(0, \sigma_\nu)$. Before agents start their first job, they receive a signal about their true ability for each occupation. We refer to this as the educational signal, though it could represent any occupation-specific knowledge gained prior to the labor market, perhaps from the media, internet, school or other sources. The accuracy of this signal may be affected by changes in factors such as the availability of information technology such as the Internet, or quality and level of schooling. The educational signal for each occupation e^j is normally distributed and centered around the true match quality: $e^j \sim \mathbb{N}(\nu^j, \frac{1}{\tau_e})$. τ_e represents the precision of the educational signal: the higher the precision, the lower the variance of the noise, so the more information it contains regarding the true match quality. After receiving the educational signal and before choosing their first occupation, the agent forms their belief and precision about their match quality for occupation j:

$$m_0^j = \frac{\tau_e^2 e^j}{1/\sigma_\nu^2 + \tau_e^2} \tag{2}$$

$$(\tau_0^j)^2 = 1/\sigma_\nu^2 + \tau_e^2 \tag{3}$$

Where m denotes the mean of the belief and τ denotes the precision. The subscript 0 means that the agent has worked at occupation j zero times, so this is the agent's prior for each

[20] We compute the agent's problem via value function iteration on $V(x,j)$. At age $T+1$, $V=0$ and the value function is computed using backward induction. Taking advantage of this property of the type I extreme value distribution and iterating over value V rather than W, the problem is significantly simplified since the probability of choosing certain occupations can be described analytically once the state is specified.

occupation.

Individuals choose their occupations based on their beliefs. When an occupation j is chosen, the agent receives wage $w(x, j)$:

$$\log w(x,j) = \psi(x,j) + \underbrace{\nu^j + \varepsilon^j}_{\theta^j} \tag{4}$$

where ψ is a deterministic state and occupation choice specific life cycle component, and ν^j is the agent and occupation specific match quality which stays invariant throughout lifecycle. ε^j is a wage innovation, and it is independently and identically distributed across occupations and agent states, drawn from a random normal distribution: $\varepsilon^j \sim \mathbb{N}(0, \sigma_\varepsilon)$. Individuals don't know their true match quality ν^j, but do know the structure of wages, and so use wages as a signal to infer the matching quality ν_j and update their current beliefs. Specifically, they know the life cycle component ψ, and therefore they can observe $\theta^j = \nu^j + \varepsilon^j$. Using θ^j as a signal, agents update their beliefs about occupation j using Bayesian learning. For simplicity, we assume that the match quality terms (ν^j) are independent from each other, so learning about occupation j only happens when agents are working at j. This framework can be easily extended to a setting where agents can learn about other occupations while working at similar occupations by allowing ν^j to be correlated with each other.[21]

Because both the match quality and the innovation are normally distributed, the signal θ is also normally distributed. Furthermore, since both the prior and the signal are normally distributed, the posterior distribution after any number of signals will also be normally distributed. The posterior distribution of beliefs about occupation j after receiving n signals (of j) can be completely described by its mean m_n^j and variance $\frac{1}{\tau_n^j}$.Using Bayes' theorem and the definitions of normal densities, one can describe how beliefs and precision evolve:

$$m_n^j = \begin{cases} \frac{(\tau_{n-1}^j)^2 m_{n-1}^j + \frac{1}{\sigma_\varepsilon^2}\theta_n^j}{(\tau_0^j)^2 + n\frac{1}{\sigma_\varepsilon^2}} & \text{if occupation j is chosen this period} \\ \\ m_{n-1}^j & \text{if occupation j is NOT chosen this period} \end{cases}$$

[21] If agents can learn about occupation j' while working at a similar occupation j, this setup could bias our estimation of switching costs, as agents may not switch due to sufficient learning rather than high switching costs.

$$(\tau_n^j)^2 = \begin{cases} (\tau_{n-1}^j)^2 + \frac{1}{\sigma_\varepsilon^2} \\ = (\tau_0^j)^2 + n\frac{1}{\sigma_\varepsilon^2} & \text{if occupation j is chosen this period} \\ \\ (\tau_{n-1}^j)^2 & \text{if occupation j is NOT chosen this period} \end{cases}$$

The conditional distribution of the time t signal for occupation j, θ_t^j, given the information available at the end of period t-1 (beginning of period t), is normally distributed with a mean and variance given by

$$\mathbb{E}\Big[\theta_t^j \mid j, m_t^j, n_t^j\Big] = m_t^j \tag{5}$$

$$Var\Big[\theta_t^j \mid j, m_t^j, n_t^j\Big] = \sigma_\varepsilon^2 + \frac{1}{(\tau_n^j)^2} \tag{6}$$

Notice that the precision term τ, which is the inverse of the variance of the belief, can be exactly derived once n (the number of periods one works at an occupation) is known.

To sum up, agents' state x_t at the begining of period t (end of period t-1) is

$$x_t = \{o_t, m_t^1, ..., m_t^J, n_t^1, ...n_t^J, a\}$$

and agents choose occupation j_t for period t at the end of period $t-1$. It is worth stressing that o_t is the occupation that the agent worked at the beginning of period t before making switching decisions. The time line of the agent's problem is shown in Figure 9. Specifically, the agent enters period t with the state x_t, which includes its occupation last period, age, as well as his beliefs on all of the occupations. The agent then observes their preference shock vector, $\zeta_t = \{\zeta_t^1, \zeta_t^2, ...\zeta_t^J\}$. Given the realized preference shocks and current state, they choose an occupation that they wishe to work at in period t. The agent will then receive a wage and use it as a signal to update their belief about j. Lastly, the agent pays the switching cost if they decided to switch occupations.

Switching Costs Let $\kappa(x, j)$ denote the switching costs, which consist of three components. The first is age-dependent switching friction, denoted $\kappa(a)$. Switching costs may vary by age: older workers might face lower costs due to greater social resources or job-search experience, or higher costs due to family constraints or slower learning. The second component is the occupational skill distance, $\Delta(o, j)$, capturing that switching between occupations with vastly different skill sets is more costly. For example, switching from mathematician to economist is likely easier than switching from waiter to economist, as the required skills are more similar in the former case. The third component, $\gamma(j,t)$, is a destination-specific cost that varies over time, reflecting differences in entrance costs such as licensing requirements. These costs apply to all individuals entering the occupation, regardless of age or previous job.

Switching costs are incurred only when actual occupation switches occur, represented by the indicator function $\mathbf{1}_{o\neq j}$. Thus, the total occupational switching cost is:

$$\kappa(x,j) = (\kappa(a) + \alpha\Delta(o,j) + \gamma(j,t))\mathbf{1}_{o\neq j}$$

3.2 Model Mechanisms

What leads an agent to switch occupations? First, a low realization of the wage signal θ may prompt a switch. A low signal causes the worker to lower their belief about match quality in their current occupation and re-rank occupations based on expected future income. This revision increases the relative belief in abilities for other occupations. If the updated belief is large enough to outweigh the switching costs, the agent switches.

Second, a low realization of the exogenous preference shock ζ in the current occupation, relative to others, can trigger a switch, especially if the agent doesn't strongly favor one occupation over another. Third, the agent may switch to explore alternatives. In the model, occupational choices are made before wage realizations, based on expected wages. Uncertainty about match quality can lead to a high expected wage in occupations where the agent is uncertain, even if their mean belief about their ability is low. This perceived high value may drive agents to explore such occupations.

Why have workers switched occupations less frequently over time? The rise of information technology since the early 1990s may have increased the precision of the worker's educational signal τ_e. With better information, agents are more accurately able to assess which occupations suit their abilities and interests, reducing the likelihood of encountering low wage signals (as match quality directly affects wages) and thus reducing switching via the first mechanism.

Additionally, increased information reduces the need to switch for exploration, as it lowers uncertainty across occupations. Higher switching costs can also contribute to reduced occupational mobility. When faced with a low wage signal or preference shock, a worker who might otherwise switch could now find the costs prohibitive, leading to lower switching rates and potentially lower overall matching rates. The next section will focus on these two mechanisms—changes in information technology and switching costs—and quantify their impact on aggregate and age-specific occupational switching rates.

3.3 Estimation Strategy

To examine changes in switching rates over time, it is essential to model and estimate how conditions evolve as new cohorts enter the labor force. A particular switching rate or information structure in 1995 may affect younger workers differently than older workers, and workers entering the labor force in 1995 will encounter different switching rates than those entering in 2010. Since both aggregate and life-cycle switching rates change over time—potentially in response to evolving economic conditions—a model addressing this issue benefits from using agent-level data across multiple cohorts.

This paper uses the SIPP survey as the primary data source for model estimation. The SIPP offers several advantages over alternative data sets for this analysis: it covers the entire period of interest (from the early 1990s to the early 2010s), has a large nationally representative sample, and its short panel structure, along with rich variables, allows for tracking occupational movements and wage changes—key elements for identification in this paper. Additionally, SIPP contains data for many cohorts, which is crucial for capturing changes in information and switching costs. By contrast, other available public data sets are less suitable for this analysis.[22]

However, the SIPP has a notable limitation: its panel structure is short, meaning agents cannot be tracked for more than three years. A common approach to analyzing age profiles with cross-sectional data, especially with short panels, is to assume that each cross-section represents a steady-state distribution over age. The idea is that individuals before a particular period faced one set of conditions, while individuals afterward faced a different set. Yet, this assumption is overly restrictive and cannot be applied here given the time frame of interest. This paper investigates changes in occupational mobility over the past 20 years, during which many agents present in earlier cross-sections also appear in later ones. For example, individuals who were 20 years old in 1993 are 40 years old in 2013. It is unrea-

[22]For instance, the PSID and NLSY have longer panel structures but smaller sample sizes and fewer cohorts. The CPS offers higher interview frequency but lacks detailed wage information.

sonable to assume two distinct steady states across these 20 years, as this would imply that the same agents faced two different sets of conditions in the two steady-state analyses. The 40-year-olds in 2013 faced the same initial conditions as the 20-year-olds in 1993.

To address this issue, we construct synthetic cohort statistics, as shown in Figure 10, and assume that time-varying parameters follow a growth path, detailed in the next subsection. Given these estimated parameter-driven growth paths, agents' optimal life-cycle occupational choices are solved for all cohorts between 1991 and 2013.[23] We estimate the model using synthetic cohort data, and the following subsection summarizes the parameters and assumptions employed in the estimation process.

3.4 Parameters and Assumptions

The agent's problem over time is governed by the following sets of parameters:

1. $\tau_{e,t}$ – precision of the educational signal, varies over time
2. $\kappa_t(x, j)$ – occupational switching cost, varies by time, occupation, and agent states
3. $\sigma_{\varepsilon,t}$ – standard deviation of wage innovations, varies by time
4. $\psi_t(x, j)$ – life-cycle wage component, varies by time, occupation, and agent states
5. σ_ν – standard deviation of initial match quality, time-invariant
6. β – discount rate, time-invariant

We follow the literature and set the agent's discount rate to $\beta = 0.986$, corresponding to an annual rate of 0.96. The remaining parameters are jointly estimated within the model. The model is estimated using all SIPP panels from 1991 to 2013 to capture trends over time. All parameters are assumed to be time-variant, except for σ_ν, as there is no clear theoretical or empirical evidence suggesting that the dispersion of initial match quality has changed. We assume that the time-varying parameters follow a piecewise linear growth path, with

[23] Specifically, we consider 58 cohorts, assuming that agents enter the labor market at age 20 and retire at age 55. This spans cohorts from those who were 55 years old in 1991 (the earliest cohort we observe in the data) to those who were 20 years old in 2013 (the latest cohort).

different growth rates allowed before and after 1995. The break point is set at 1995, as this paper primarily examines labor market changes between 1993 and 2013.[24]

While occupational switching costs κ and life-cycle wage components ψ typically vary by occupation, this introduces a large number of parameters to estimate. Since the primary focus of this paper is on shifts in aggregate switching rates across age, we simplify the model without significant loss of generality. We do not directly estimate occupation-specific switching rates or wage profiles. Instead, we assume $\Delta(o, j) = 0 \,\forall\, o,\, j$ and $\gamma(j, t) = \gamma(t) \,\forall\, j$. Thus, the estimated switching costs reflect an average across occupations and vary only by time and age.[25] This simplification still enables us to identify the contribution of average switching costs to changes in switching rates and welfare by age. After these simplifications, we estimate 18 parameters in total:

$$\tau_e = \tau_0 + \tau_1 \cdot year\mathbf{1}_{year\leq 1995} + \tau_2 \cdot year\mathbf{1}_{year>1995}$$
$$\kappa = \kappa_0 + \kappa_{01} \cdot year\mathbf{1}_{year>1995} + \kappa_{02} \cdot year\mathbf{1}_{year\geq 1995} + \kappa_1 \cdot age + \kappa_2 \cdot age^2$$
$$\psi = \psi_0 + \psi_1 \cdot age + \psi_2 \cdot age^2 + \psi_3 \cdot year + \psi_4 \cdot year^2 + \psi_5 \cdot age \times year$$
$$\sigma_\varepsilon = \sigma_0 + \sigma_1 \cdot year\mathbf{1}_{year\leq 1995} + \sigma_2 \cdot year\mathbf{1}_{year>1995}$$
$$\sigma_\nu$$

The structure of the life-cycle wage component follows Kambourov and Manovskii (2005). We estimate the parameters using the Simulated Method of Moments (SMM). The computation is demanding, given the large state space for each cohort (three occupations, five grid points for beliefs, and 35 years of working life), and there are 58 separate cohort problems to solve for each parameter guess.[26] However, calibrating the model to all synthetic cohorts provides significant advantages over assuming a traditional steady-state framework, which would be overly restrictive for this analysis. By utilizing all available public data, we capture the trends and transitions in occupational mobility over the past 20 years. We also simulate cross-sectional economies from different cohorts, allowing for direct comparison between

[24]Piecewise linear trends are widely used in the literature to capture different phases of economic changes across periods, as seen in Blundell and Preston (1998) and Card and DiNardo (2002). This approach efficiently captures shifts, such as the rise of information technology in the 1990s, while reducing the number of parameters to be estimated compared to more flexible frameworks. We also explored alternative breakpoints, but the results are not sensitive to this choice.

[25]This simplification is also motivated by concerns over the computational burden. Even with only three occupations, the state space for each cohort is very large. Using broad occupational groups in our analysis does not provide much insight into occupation-specific dynamics but offers more meaningful inference about the average across all occupations.

[26]The state space for each cohort is $3 \times 5^3 \times 35^3 = 16,078,125$.

observed and simulated data, and for running policy experiments.

One potential concern in comparing 1993 to 2013 is the timing of the first period. The NBER recession ended in April 1991, which might affect switching rates cyclically, potentially causing observed rates to deviate from natural rates. However, since the data is averaged over 1992–1993, this should mitigate any recession effects. Moreover, if the recession had an impact, it would likely suppress switching rates, meaning the observed decline in switching between the two periods may be underestimated, providing a lower bound for the effects of information and switching costs on occupational mobility.

The next subsection discusses identification, followed by estimation results and counterfactual experiments.

3.5 Identification

The five sets of parameters to be estimated are: $\{\tau_e,\ \kappa,\ \psi,\ \sigma_\varepsilon,\ \sigma_\nu\}$. Among these, τ_e (the precision of information) and κ (the switching costs) are the central focus of this paper. The key question is: how much of the decline in occupational switching rates can be attributed to improvements in information, as opposed to increases in switching costs? Thus, the core challenge in identification is to separately distinguish the effects of these two factors.

If switching costs did not vary with age, the slope of the switching rate age profile would be sufficient for identification. Information improvements primarily affect younger workers, while older workers are less impacted. However, when switching costs vary by age, the occupational switching rate age profile alone is insufficient for identification—this is illustrated in the left panel of Figure 11. The blue dashed line represents the model-generated age profile of occupational switching rates.[27] When the precision of information (τ_e) increases, the dashed black line shows that the decline in switching rates primarily affects younger workers. However, when switching costs increase and vary by age, the solid red line shows a similar tilting of the age profile. Both mechanisms—improvements in information and increases in switching costs—produce similar effects on the switching rate age profile, making identification more difficult.

However, the right panel of Figure 11 shows that identification can be achieved by examining the impact of these mechanisms on wage profiles. Wages provide a useful source of

[27] The parameters used to generate this age profile are estimated to match the 1993 cross-sectional occupational switching rates.

identification because they reflect both workers' expectations about future gains (for switching costs) and retrospective corrections to initial errors in occupation choice (for information precision). The blue dashed line represents average wage changes associated with occupational switches under the baseline model. In contrast, changes in information precision and switching costs drive wage changes in opposite directions. This is intuitive: higher switching costs lead to larger expected wage gains for those who switch, as only those expecting substantial gains will switch. These higher gains can be seen as compensation for the increased costs. Conversely, more precise information reduces the observed wage gain from switching because workers make smaller corrections when they switch, having been "less wrong" about their initial occupational match quality.

Although the model's Bayesian learning structure makes a full analytical proof of identification difficult, we provide a simplified analytical proof to build intuition. Consider a case where agents work for only two periods and choose between two occupations, a and b. Match quality is drawn from a distribution $\nu^j \sim \mathbb{N}(0, \sigma_\nu), \quad j \in \{a, b\}$, and agents receive an educational signal $e^j = \nu^j + \eta^j, \quad \eta^j \sim \mathbb{N}(0, \frac{1}{\tau_e})$. Agents choose their first-period occupation j after receiving the signal and receive wages based on their match quality, $w^j = \nu^j$. Agents fully learn about their match quality in both occupations by the second period. The probability of switching from a to b is:

$$\begin{aligned}
\Pr(a \to b) &= \Pr(e^a > e^b \;\&\; \nu^a < \nu^b - \kappa) \\
&= \Pr(\kappa < \nu^b - \nu^a < \eta^a - \eta^b)
\end{aligned}$$

Due to the symmetry of the problem, $\Pr(a \to b) = \Pr(b \to a)$. The switching probability depends on the joint likelihood that workers initially choose occupation a and then switch to b after learning about their true match quality. Since ν^a, ν^b, η^a, and η^b are normally distributed, we have:

$$\nu^b - \nu^a \sim \mathbb{N}(0, \sqrt{2}\sigma_\nu), \quad \eta^a - \eta^b \sim \mathbb{N}(0, \frac{\sqrt{2}}{\tau_e})$$

From this, it is clear that the probability of switching decreases as κ increases. Similarly, as τ_e increases, the standard deviation of η decreases, which also lowers the switching probability for $\kappa > 0$. Therefore, both higher switching costs and better information reduce the likelihood of switching, corresponding to the patterns in the full model.

To demonstrate identification, we must also examine the average wage gains associated with switching:

$$\begin{aligned}
&\mathbb{E}\Big[\nu^b - \nu^a \mid \mathbb{E}(w_1^b < w_1^a),\ \mathbb{E}(w_2^b > w_2^a)\Big] \\
&= \mathbb{E}\Big[\nu^b - \nu^a \mid e^b < e^a,\ \nu^b - \kappa \geq \nu^a\Big] \\
&= \mathbb{E}\Big[\nu^b - \nu^a \mid \kappa < \nu^b - \nu^a < \eta^a - \eta^b\Big]
\end{aligned}$$

As κ increases, this conditional expectation rises, as the wage increases are truncated on the left. On the other hand, more precise information (a decrease in the standard deviation of η) lowers the conditional expectation. Thus, the average wage gain from switching rises with switching costs but falls with greater information precision. By using both occupational switching rates and the wage gains from switching, we can separately identify the effects of information precision and switching costs, even when switching costs vary by age.

This simplified two-period model provides clear intuition on how both mechanisms influence switching rates and wages. In the full model, identification becomes more complex because workers update their beliefs over multiple periods. Even small modifications—such as assuming that workers only learn about occupations they actually choose—make solving the identification problem analytically intractable. Therefore, in the full model, identification is demonstrated numerically, as shown in Figure 11. Despite this complexity, the core intuition from the simplified model holds: wage gains reflect both switching costs and information precision, allowing us to disentangle the two mechanisms in a more realistic setting.

Identification of the other parameters is more straightforward. ψ, σ_ε, and σ_ν directly influence wages and can be identified by targeting the age profiles of average wages and wage variance. In the next section, we present the estimation results and model fit, followed by results from various counterfactual experiments.

4 Estimation Results and Experiments

This section presents the results from the basic model calibration described above, followed by counterfactual exercises conducted using the calibrated model.

4.1 Calibration and Model Fit

Our primary focus is on the level and trend of information precision (τ_e) and switching costs (κ). The piecewise linear trend assumed in this paper allows for different trends before and after 1995, although it does not require them to differ. The model remains flexible, allowing for parameter trends to either increase or decrease. We also accommodate the possibility of negative switching costs, such as switching compensation.

The calibrated growth paths for τ_e and κ are shown in the left and right panels of Figure 12, respectively. While the absolute level of information precision is model-specific and cannot be directly interpreted, the key result is the relative change: information precision has increased by more than 50% over the past 20 years. The calibrated values of switching costs are reasonable and consistent with the literature. Over the past 20 years, switching costs increased from about \$1,500 to \$1,800 on average, representing a rise from 60% to 65% of the average monthly wage. This increase is entirely inferred from the model, but we rationalize part of it using observable changes in licensing costs. For example, average initial licensing fees increased by \$117 between 1995 and 2013. The \$300 increase in switching costs estimated by the model reflects not only licensing costs but also broader factors such as changes in educational requirements, examination fees, and retraining costs. Section 5.5 explores the impact of licensing changes in further detail.

Table 2 summarizes the remaining calibrated parameters. The model fits the data well, as shown in Figure 13, which compares the model-generated cohort switching rates with the synthetic cohort rates from the data. The figure presents switching rates for cohorts from 2013 (20-year-olds in 2013) back to 1956 (55-year-olds in 1991). The solid line replicates the cohort switching rates (same as in Figure 10), while the red dashed line represents the model's fit. The model accurately captures both the slope and level of switching rates across successive cohorts.

Using the simulated agents from 58 consecutive cohorts, we construct successive annual cross-sections of the simulated economy and compare them with the observed cross-sectional data. Figure 14 demonstrates that the model successfully replicates key features of the data. The left panel shows the decline in occupational switching rates between 1993 and 2013 across all ages, with a particularly pronounced drop among younger workers compared to older ones. The right panel displays the average log wage changes from occupational switching across two time periods and all age groups. In both panels, the simulation matches the data well. With this validation, we are now ready to run the counterfactual experiments.

4.2 Counterfactual Occupational Switching Rates

The counterfactual experiments use the model to measure the contributions of initial information and switching costs to changes in occupational switching rates and worker welfare. These exercises can be viewed as structural decompositions. For each factor, we hold that factor at its 1995 level while allowing all other factors to shift to their 2013 levels. We also hold both information and switching costs at their 1995 levels while allowing other factors to evolve. The results of the counterfactual experiments for information precision and switching costs are presented in the left and right panels of Figure 15, respectively. These experiments address the following question: if starting in 1995, neither (or either) information precision nor (or) switching costs had changed, what would switching rates and worker welfare look like in 2013? In this subsection, we focus on the effects of these factors on switching rates, while worker welfare changes are discussed in the next subsection.

By holding information precision at its 1995 level, we isolate its effect on switching rates, as shown in Figure 16. The solid lines correspond to the model values in the left panel of Figure 14, while the blue dashed line shows the counterfactual occupational switching rate age profile. The area between the blue dashed line and the solid red line illustrates the impact of changes in information precision over time. These changes predominantly affect younger workers and have no effect on cohorts that entered the labor market before 1995.

Compared to information precision, the impact of increased switching costs is much more pronounced. The effect of switching costs on occupational switching rates by age is shown in Figure 17. Similar to Figure 16, the red dashed lines represent the counterfactual switching rates for each age group, assuming switching costs (κ) were held at their 1995 levels while other factors progressed to their 2013 levels. The shaded area between the red dashed line and the solid bottom line represents the effect of rising switching costs. Unlike the information experiment, changes in switching costs affect all workers across the economy, and the effect is substantial. Furthermore, changes in switching costs not only influence workers in 2013 but also those in 1993, regardless of cohort. The black dashed line in Figure 17 illustrates this effect: workers in 1993 anticipate a future change in switching costs and adjust their behavior accordingly. For instance, 20-year-olds in 1993, knowing that switching costs will flatten in two years, are more likely to switch occupations than they would have been if they had expected future switching costs to continue rising.

The final counterfactual experiment examines the joint effect of switching costs and information precision. Figure 18 shows the combined effects of both factors on switching rates by age. The blue dashed line represents the joint effect, while the red dashed line represents the switching cost effect, as shown in Figure 17.[28] A comparison of the two factors reveals that switching costs account for a significantly larger effect, influencing workers of all ages. Information precision also contributes to the decline, but its effect is considerably smaller since it primarily affects younger workers.

The aggregate effects of these two factors on switching rates are summarized in Table 3. The first column shows the observed data for each year, calculated from the SIPP panels. The second column presents the same statistics calculated using the simulated data from the calibrated model. These statistics are constructed using the simulated worker panel and demographic shares from the US Census Bureau. For example, to calculate the aggregate switching rate in the calibrated model for 1993, we select random subsamples from the simulated worker panel according to the census population shares for 1993 and calculate the switching rate from this new representative cross-section. Expected lifetime income is calculated as the mean total lifetime income for the entire simulated panel. The discussion on lifecycle income and welfare will be expanded in the next section. Columns three through five show the main counterfactual exercises described above.

The rows of switching rate show that the calibrated model closely matches the data in both periods. Column three presents the information counterfactual (τ_e), examining the contribution of changes in the precision of the educational signal. In this counterfactual, the switching rate in 1993 remains at 6.11%, identical to the rate in the model column, since holding the information precision at its 1995 level does not affect agents in 1993.[29] However, the counterfactual switching rate in 2013 is 3.5%, which is 0.21 percentage points higher than in the estimated model. This suggests that changes in information precision account for 7.6% of the total decline in occupational switching rates.

Column four (κ) of Table 3 details the corresponding counterfactual for switching costs. The results suggest that most of the decline in switching rates (71.8%) is due to increased switching costs.[30] As mentioned earlier, the switching cost counterfactual differs from the information counterfactual: in this case, holding switching costs at their 1995 levels affects agents in both the 2013 and 1993 cross-sections. As discussed, agents in 1993 anticipate future changes in switching costs and adjust their behavior. The 6.41% switching rate in 1993 reflects this effect—workers, expecting future declines in switching costs, choose to

[28] When decomposing the joint effect in reverse order—first isolating the information effect and then switching costs—the counterfactual effects for both factors remain nearly unchanged.

[29] This is not the case in the switching cost counterfactual, as discussed earlier in this section.

[30] The percentages are calculated as follows: $7.6\% = 1 - \frac{6.11-3.5}{6.11-3.29}$, and $71.8\% = 1 - \frac{6.41-5.62}{6.11-3.29}$.

switch more frequently (6.41%) than they would have under the estimated economy (6.11%).

The final counterfactual (τ_e, κ, column five) examines the joint effect of changes in both signal quality and switching costs, compared to changes in the income process. The joint effect accounts for up to 80.2% of the total decline in occupational switching rates. Since both factors push the switching rate in the same direction, the joint effect accounts for most of the observed decline in mobility rates.

These results suggest that both changes in switching costs and improvements in initial information played significant roles in the observed decrease in switching rates, while changes in demographics played a minor role.

4.3 Counterfactual Wage Implications

The counterfactual exercises above illustrate how changes in information precision and switching costs affect workers' occupational switching rates. However, the more critical question is how these changes have impacted worker welfare. Workers switch occupations to find a better match, which can lead to improved productivity, higher wages, and increased welfare. This section examines the effects of changes in information precision and switching costs on wages and welfare.

The main calibration and counterfactual results are presented in Table 3. We focus on three key aggregate measures: mean monthly income, mean annual income over the 20-year period, and expected lifetime income for different cohorts. For mean monthly income, we compare data, model results, and counterfactual experiments for 1993 and 2013. The mean incomes in the estimated model fit the data well. In the data, average monthly income rises modestly from $2,498 to $2,676, and in the model, it increases similarly from $2,495 to $2,745. As with the switching rate results, the counterfactual results for mean income are presented in columns three through five.

The effect of lower information precision is shown in the "Counterfactual τ_e" column. While the magnitude of the change is small — from $2,745 to $2,743 — it is clear that higher information precision improves welfare. The small change in average income masks larger welfare impacts on certain groups, particularly younger workers or those in transition, who benefit significantly from better matching under improved information precision. On the other hand, declines in switching rates due to higher switching costs tend to reduce welfare. When switching costs are held at their lower 1995 level, as shown in the "Counterfactual κ"

column, mean monthly income increases. The impact of switching costs on income is larger than the effect of information: on aggregate, lower switching costs result in a \$25 increase in mean monthly income from 1993 to 2013.

While the joint effects on switching rates push in the same direction, they have opposite impacts on welfare. Increased information precision since 1995 has improved welfare, while rising switching costs have reduced it. Jointly, the increase in mean income in the counterfactual relative to the data is driven by the larger impact of switching costs, which dominates the direction of welfare change. The magnitude of welfare change is small on average but much larger when measured across the economy or when looking at workers who experienced changes in their welfare. It is important to note that small average changes can conceal large aggregate welfare effects. Many workers are not directly affected by changes in information precision or switching costs, but those who were close to indifference between switching or not switching—such as marginal workers—were much more sensitive to these changes.

The "Mean Annual Income" variable is similar to the previous measure, but here we calculate the average annual income for each year and then average it over the entire period from 1993 to 2013. This measure captures the potential GDP loss from mismatches: if wages reflect productivity, this shows the gain or loss in output from more mismatched workers (τ_e counterfactual) or better-matched workers (κ counterfactual). The income gain comes from increased productivity as workers are better matched, either due to freer movement in a low switching cost environment or better initial matches. These improvements in matching have clear macroeconomic implications, as better matches contribute to higher overall productivity, which, in turn, drives GDP growth. For example, the "Model" column shows that the mean annual income for workers aged 20 to 55 from 1993 to 2013 was \$31,871, which closely matches the observed data (\$31,098). In the first counterfactual, mean annual income would be \$13 lower. Aggregated over 20 years and the entire prime-aged (20-55) full-time workforce, this could amount to \$22.1 billion in lost wages due to poorer information, disproportionately affecting young workers. The κ counterfactual suggests that increased switching costs have reduced worker incomes by a factor of 10 compared to the information effect over this period.

These aggregate effects are illustrated in Figure 19. The table shows mean annual income from 1993 to 2013, while the left panel of Figure 19 shows the year-by-year difference in average annual income between the estimated economy and the κ counterfactual. For example, in 2013, mean annual income would have been \$300 higher in a low-switching-cost environment compared to the calibrated economy, highlighting the switching cost effect. By multiplying total employment by the difference between the calibrated and counterfactual economies, we can estimate the total loss in wages due to increased switching costs. The right panel of Figure 19 shows this wage loss each year due to rising switching costs. In 2013, this loss represents about 0.2% of real GDP.

Overall, increases in information precision provided modest improvements in average income and welfare, beyond what would be expected from changes in the income process alone. This suggests that policies targeting information frictions—particularly those faced by workers early in their careers—can play a significant role in improving welfare and reducing labor misallocation. In contrast, the increase in switching costs had a much larger negative effect on average income and welfare. Policies aimed at reducing switching costs could help workers find more productive occupational matches, thereby increasing wages and improving welfare. These findings have important policy implications, suggesting that reducing labor market frictions like switching costs can substantially boost both individual welfare and macroeconomic outcomes. In Section 4.5, we explore the welfare effects of changes in switching costs using occupational licensing as an example.

4.4 Lifetime Welfare Analysis

This section investigates the lifetime welfare effects on workers. The final panel of Table 3 shows the expected lifetime income for different cohorts, where the year refers to the labor market entry year. The results for lifetime income are consistent with the aggregate analysis: improved information increases workers' welfare, while higher switching costs reduce it. For example, workers entering the labor market in 2003 would experience a $2,000 lifetime income loss on average if information had not improved. Conversely, if switching costs had not increased, workers would gain an average of $9,000 over their lifetime. These figures represent simple averages across all agents in the economy, but many workers are unaffected by these environmental changes. This is important to note because not all workers are bound by switching costs—some would not switch occupations regardless of the labor market conditions. As a result, workers who are not affected by the changes in switching costs or information experience no real income loss. However, if we focus on workers whose behavior is actually affected by these changes, the lifetime income loss is much more significant. For workers who are on the margin — those who adjust their behavior in response to changes in switching costs or information — the lifetime income loss can be as high as $20,000 per person.

The previous experiments capture workers' monetary utility changes, but occupational switching is driven by both monetary factors and non-pecuniary preferences, for example, factors such as job satisfaction, work-life balance, or personal fulfillment, which play a crucial role in workers' overall welfare, and are captured by the non-pecuniary component in workers' utility function. These non-monetary aspects often cannot be directly observed in the data. However, workers' occupational choices and realized wages reflect these preferences indirectly. By applying compensating variation analysis to the estimated model, we can infer the total welfare effects, including both monetary and non-pecuniary utility.

Take the switching cost change as an example. The intuition behind the compensating variation exercise is straightforward: in the counterfactual where switching costs are held at their 1995 level, workers face lower switching costs, allowing them to move more freely, earn higher wages (as shown in the previous subsection), and experience higher utility. Compensating variation measures how much monetary compensation workers facing higher switching costs would need to achieve the same utility level as they would under lower switching costs.

The compensation value varies by the worker's labor market entry year. Workers who retired before 1995 would not be affected by the switching cost changes, so their compensation is zero. In contrast, workers entering the labor market later face higher average switching costs for a longer portion of their careers and thus require more compensation. The left panel of Figure 20 shows the compensating value by labor market entry year. For workers entering the labor market in 2003, the average compensating value is $35,000 over their lifetime. This translates to a significant welfare cost: workers entering the labor market in 2003 who face the higher switching cost path effectively lose one year of mean annual wages, in constant 2000 dollars.

The average compensating value reflects the mean effect of the switching cost change across all workers. However, not all workers are equally affected. For example, workers who are well-matched in their occupations may not change jobs, regardless of switching costs, while those in poorly matched occupations may be significantly impacted. For workers who are affected by switching cost changes, the magnitude of the welfare loss can be substantial. The right panel of Figure 20 shows the mean compensating value for workers by labor market entry year, conditional on actually losing due to the switching cost increase. The black solid line represents the mean compensating value across all workers, while the red dashed-dotted line represents the mean value for those who are directly affected. Among workers entering the labor market in 2003, those who lose due to higher switching costs face an average welfare loss of approximately $60,000 over their lifetime, in constant 2000 dollars.

At the 95th percentile, the lifetime utility loss can reach $144,000 thousand dollars. The policy implications of these findings are significant. Workers who are poorly matched to their occupations or who face high switching costs are disproportionately impacted, facing large welfare losses. Addressing labor market frictions such as switching costs would not only improve individual welfare but could also contribute to greater labor market efficiency and productivity.

4.5 Occupational Licensing Effects

One common form of occupational switching cost is the requirement to obtain an occupational license. An "occupational license" is official permission from the government allowing an individual to work in a particular field. Workers typically obtain a license by fulfilling various requirements, such as completing a certain level of education, undergoing specialized training, passing standardized exams, and paying licensing fees. According to Carpenter et al. (2012), in the 1950s, only 1 in 20 U.S. workers needed government approval to pursue their chosen occupation. Today, that figure has grown to nearly one-third. Many licensing requirements may not be necessary and are often seen as a result of lobbying by practitioners to limit competition, rather than reflecting the true characteristics of the occupation (Carpenter et al. (2012)).[31]

From the early 1980s to 2012, the proportion of occupations requiring licenses across the country increased for all major occupational groups. For example, in Management and Professional occupations, the proportion of licensed occupations rose from 34% to 46%. In Service occupations, the share increased from 18% to 25%. Overall, the proportion of licensed occupations increased by nearly 10 percentage points, from 17% to 26% (Redbird (2017)). Not only has the proportion of licensed workers and occupations increased, but licensing requirements have also become more stringent in many already-licensed occupations (Han and Kleiner (2016)).

We use newly collected data from the Occupational Licensing Law Research Project (OLLRP), which provides a comprehensive view of changes in licensing requirements over time. The data includes aggregate and average licensing requirements, compiled from government documents and online databases such as LexisNexis and Careeronestop – Credentials

[31] The stringency of licensing often does not correlate with public health or safety risks. For instance, 66 occupations have greater licensure burdens than emergency medical technicians. The average cosmetologist spends 372 days in training, compared to just 33 days for an emergency medical technician (Carpenter et al. (2012)).

Center, which is sponsored by the U.S. Department of Labor. The dataset covers 45 universally licensed occupations across all 50 states and the District of Columbia.[32] The dataset tracks requirements such as minimum education, training hours, year of initial licensure, experience, required exams, continuing education, initial licensing fees, and renewal costs from 1980 to 2015. It also includes information on restrictions for former convicts, licensing board composition, and more. This rich dataset allows us to examine the impact of licensing on worker mobility and welfare.

We present summary statistics from the OLLRP in Table 4.[33] The table suggests that occupational licensing requirements increased from 1995 to 2013, corresponding to the time span of the counterfactual experiments discussed earlier. This allows us to use our estimated model to run policy experiments with the observed changes in licensing requirements. The first column of the table lists seven universally licensed occupations. The "Education" columns show the change in education requirements from 1995 to 2013. For example, in 1995, most states only required a high school diploma or less for land surveyors. By 2013, the average requirement had risen to an associate's degree. The "Initial Cost" columns show the change in initial licensing costs over the same period. The initial licensing fee for land surveyors increased by 42%, from \$82 in 1995 to \$116 in 2013, covering application fees, exam fees, and other initial costs. The "Renewal Cost" columns track changes in the cost of license renewal, with land surveyor renewal fees rising by 24%, from \$86 to \$106. Licensing requirements display considerable heterogeneity across occupations. For instance, massage therapy did not require a degree in either the 1990s or today, but renewal costs for massage therapists doubled over the past 20 years. On average, the total initial licensing cost doubled, from \$101 to \$218.[34]

We use these observed increases in licensing costs to run a policy experiment. The experiment asks: If average initial licensing costs had remained at their 1995 levels, how would workers have behaved over the past 20 years, and how would wages and welfare have been affected? While this experiment provides valuable insights, it must be interpreted with caution. On one hand, initial licensing fees represent only a small part of the total cost of licensing. The more burdensome aspects of licensing, such as required exams, training hours, and education requirements, are often the real drivers of costs (Carpenter et al.

[32]The online databases used for collecting occupational licensing requirements include WestlawNext, LexisNexis, HeinOnline, Careeronestop-Credentials Center, ABA Collateral Consequences, Way Back Machine, and Council for Higher Education Accreditation. The full list of occupations can be found in the Appendix.

[33]These statistics are calculated from a subset of 20 occupations and 30 states. The table should be considered suggestive evidence, as data collection is not yet complete.

[34]This average reflects all 20 occupations in the dataset, not just the seven shown in the table.

(2012)). Therefore, using initial costs as an indicator likely underestimates the true burden of licensing. On the other hand, these average cost changes are calculated only for fully licensed occupations. Since only about one-third of the workforce is licensed, the estimates may overstate the average effect of licensing costs on the overall economy. Despite these limitations, the results are still informative for policymakers: holding licensing costs at their 1995 levels—a total decrease of $117 relative to 2016—would have significantly altered labor market outcomes and worker welfare.

Figure 21 illustrates the effect of reduced licensing fees on aggregate occupational switching rates by age. If average licensing fees had not increased since 1995, the aggregate switching rate in the economy would have been 4.57%, compared to the actual rate of 3.29%. This suggests that changes in licensing costs alone can account for roughly one-third of the total decline in occupational switching rates from 1993 to 2013. Other potential switching costs, such as training time, geographical relocation costs, and job search expenses, further influence workers' mobility decisions and welfare.

5 Conclusion

This paper contributes to the growing literature (e.g., Molloy et al. (2016)) documenting the aggregate decline in occupational switching rates in the U.S. over the past few decades. Demographic changes such as age distribution, gender, and educational composition explain only a small portion of this decline, leaving much of it unexplained. Further analysis of public data, including CPS and SIPP, reveals that the decline in occupational switching is more pronounced among younger workers and has been consistent across consecutive cohorts over the past 20 years.

Guided by these empirical findings, we use a dynamic discrete choice model to explore two key factors potentially driving this decline: (1) rising switching costs, which could make the labor market less flexible, and (2) improved information on occupational match quality, which may result in better matches and less need for workers to switch occupations. Our estimation using SIPP data shows that both factors play a crucial role in explaining the decline, accounting for up to 80% of the total decrease in switching rates. While improvements in pre-labor market information precision significantly affect matching quality, this factor primarily influences younger workers and accounts for only 8% of the aggregate decline. In contrast, changes in switching costs, though modest, affect all workers and explain approximately 72% of the decline.

The impact of increased information precision on matching in the model may have important productivity and welfare implications that are difficult to measure directly. Using compensating variation analysis, we estimate that the total welfare change, including both monetary and non-pecuniary factors, is much larger than what is captured by lifetime income alone. The average welfare cost for workers entering the labor market between 1993 and 2013 is about 3% of lifetime income. Some workers experience even greater losses; for instance, among those who entered the labor market in 2003 and were negatively affected by higher switching costs, the 95th percentile of lifetime utility loss amounts to approximately 12% of lifetime income.

There are several policy options available to improve worker matching and welfare by increasing information access and transparency. Such policies are likely to benefit younger workers by helping them find better job matches early in their careers. For older workers, reducing occupational switching costs—such as lowering licensing fees—could be more effective in encouraging mobility when needed. For example, our analysis using data from the OLLRP shows that an average increase of $117 in initial licensing fees can explain up to one-third of the aggregate decline in occupational switching rates. However, changes in occupational licensing may have broader effects on firm surplus, wages, and consumer welfare, which warrant further analysis. Future research should focus on developing a more comprehensive general equilibrium framework to assess the full welfare implications of occupational licensing reforms.[35]

[35] Kleiner and Soltas (2023) provides a general equilibrium framework for analyzing the welfare impacts of licensing. However, this work focuses on static equilibrium rather than dynamic lifecycle analysis.

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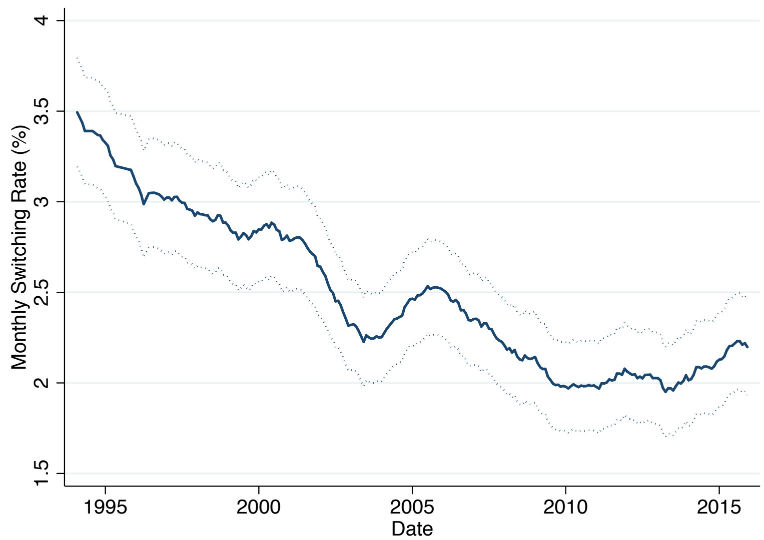
Figure 1: Monthly Occupational Switching Rate

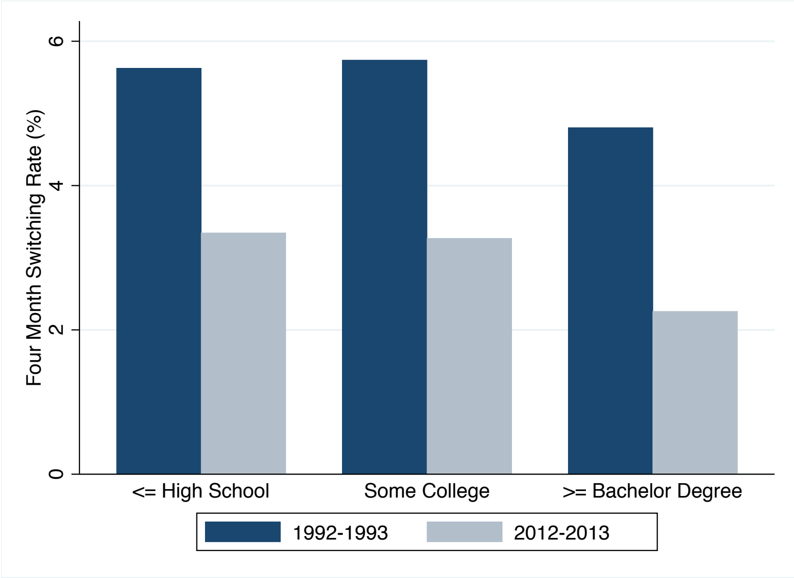


Notes: Author's calculation using the monthly CPS. The solid line shows the average monthly switching rate, and the two dash lines show the two standard deviation confidence intervals. Data sample: 20 to 64 years old male workers who are working in both month 2 and month 3 of the CPS surveys.

Figure 2: Monthly Occupational Switching Rate by Age Groups

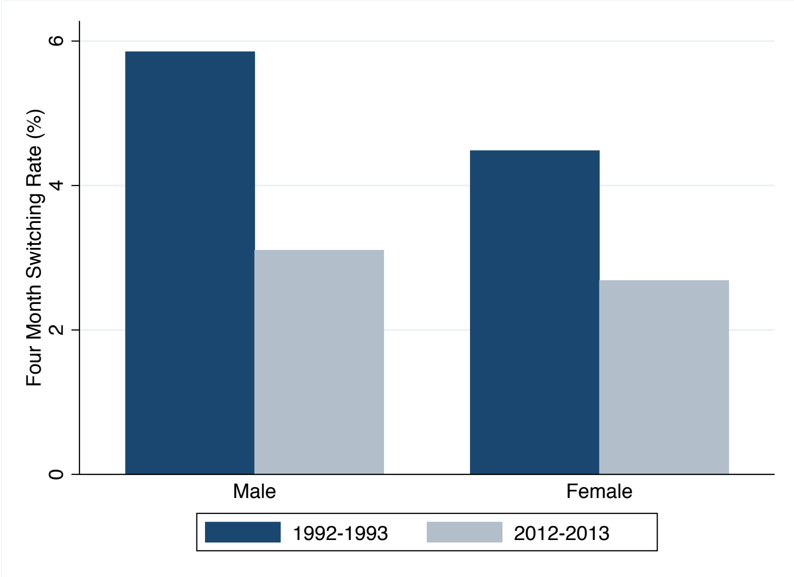
Notes: Author's calculation using the monthly CPS. Data sample: 20 to 60 years old male workers who are working in both month 2 and month 3 of the CPS surveys.

Figure 3: Occupation Switching Rate by Education Level



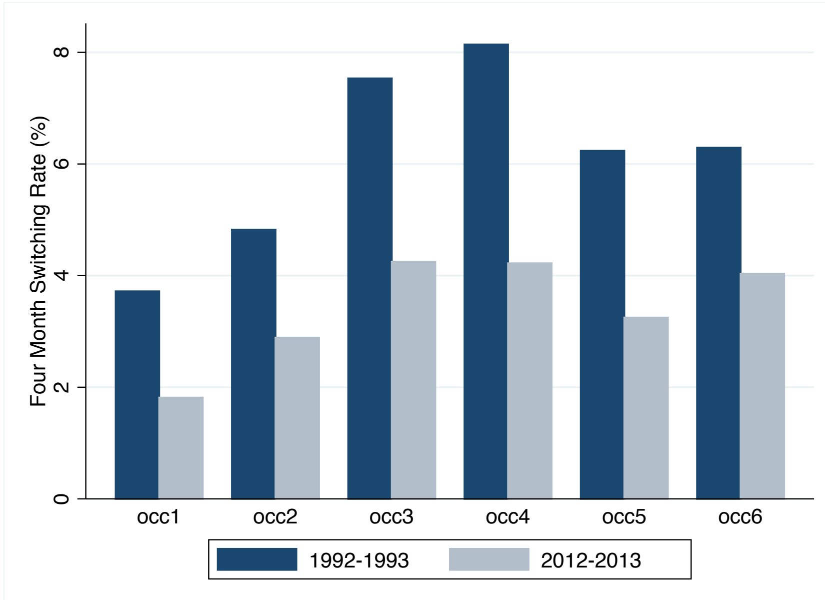
Notes: Author's calculation using SIPP. The occupation code used in constructing occupational switching rate is: Managerial and Professional, Technical Sales and Admin Support, Service Occupations, Farming Forestry an Fishing, Precision Production Craft and Repair, Operators Fabricators and Laborers

Figure 4: Occupation Switching Rate by Gender



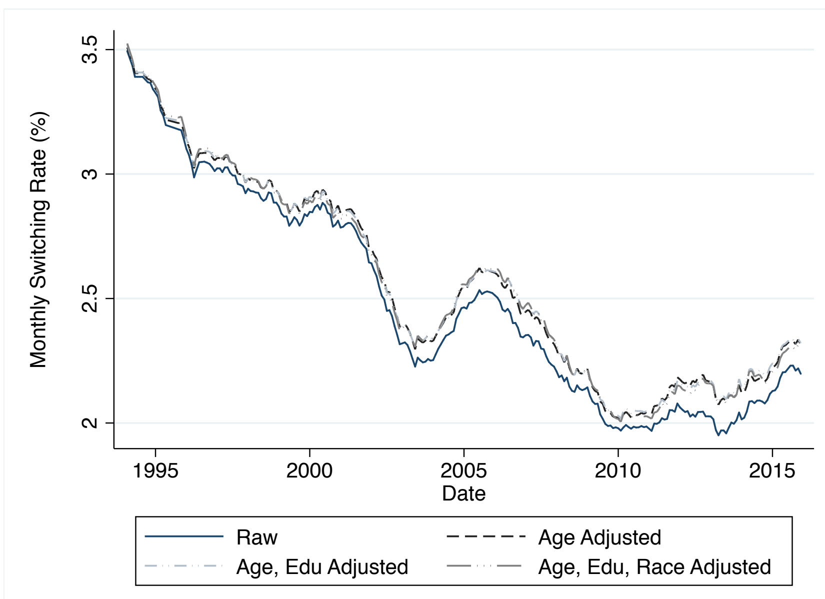
Notes: Author's calculation using SIPP. The occupation code used in constructing occupational switching rate is: Managerial and Professional, Technical Sales and Admin Support, Service Occupations, Farming Forestry an Fishing, Precision Production Craft and Repair, Operators Fabricators and Laborers

Figure 5: Occupation Switching Rate by Major Occupation group



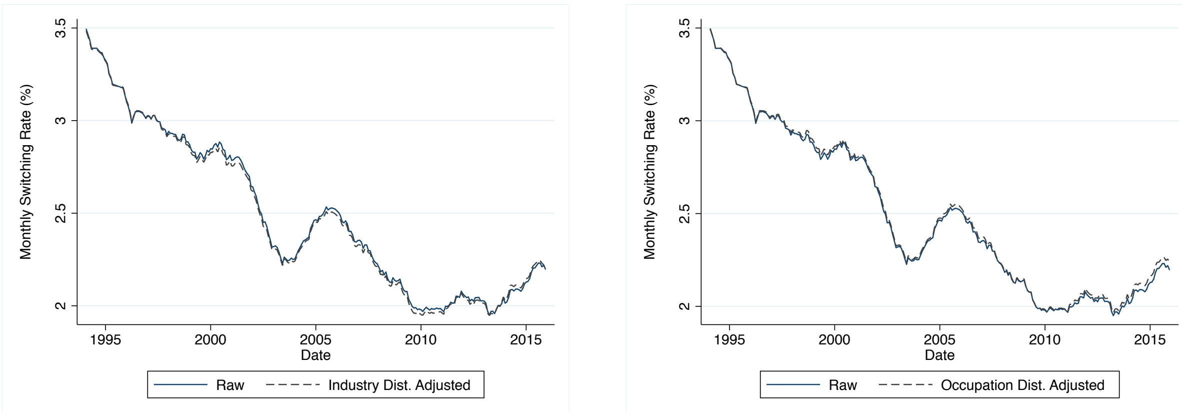
Notes: Author's calculation using SIPP. The occupation groups are: occ1: Managerial and Professional occ2: Technical Sales and Admin Support occ3: Service Occupations occ4: Farming Forestry an Fishing occ5: Precision Production Craft and Repair occ6: Operators Fabricators and Laborers

Figure 6: Occupation Switching Rate Decomposition



Notes: Author's calculation using the monthly CPS. The age groups 20-24, 25-29, 30-34, ... 60-64. The education groups are: less or equal to high school, some college or associate degrees, greater or equal to bachelor degree. The race groups are white and none-white. Data sample: 20 to 64 years old male workers who are working in both month 2 and month 3 of the CPS surveys.

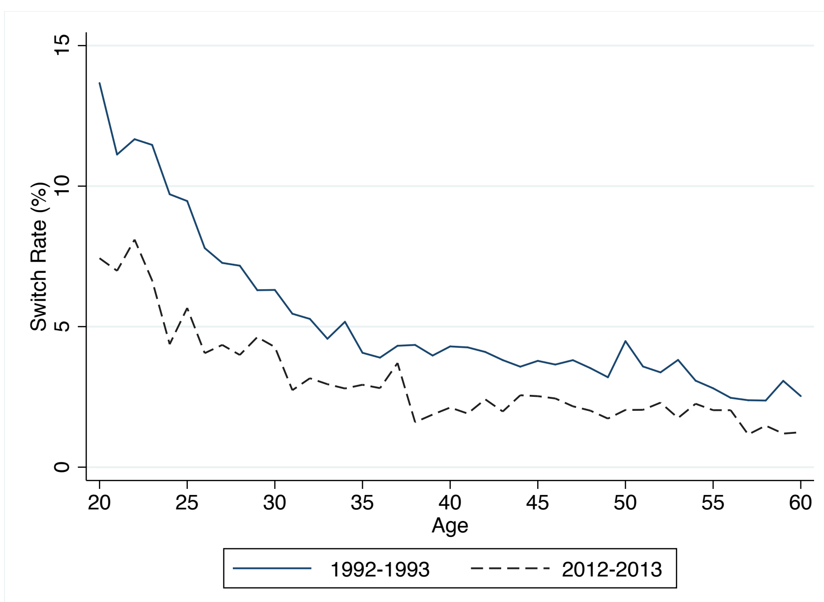
Figure 7: Occupation Switching Rate Decomposition



Adjusted by Industry Distribution Adjusted by Occupation Distribution

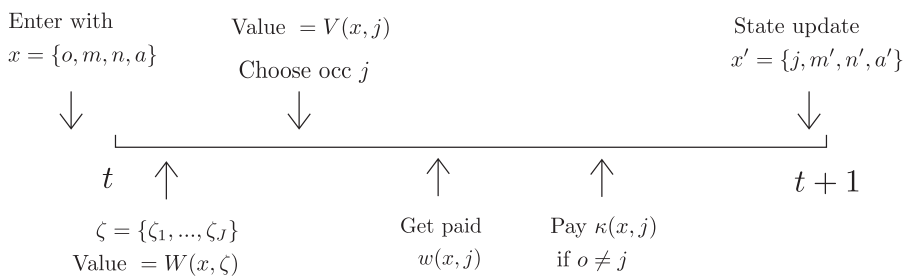
Notes: Author's calculation using the monthly CPS. The industry groups are: 1. Agriculture, Forestry and Fisheries 2. Mining 3. Construction 4. Manufacturing 5. Transportation, Communications, and Other Public Utilities 6. Wholesale Trade 7, Retail Trade 8 Finance, Insurance and Real Estate 9. Business and Repair Services 10. Personal Services 11. Entertainment and Recreation Services 12. Professional and Related Services 13. Public Administration. The occupation groups are: 1. Managerial and Professional 2. Technical sales and Administration Support 3. Service Occupations 4. Farming Forestry and Fishing 5. Precision Production, Craft and Repair 6 Operators Fabricators and Laborers. Data sample: 20 to 64 years old male workers who are working in both month 2 and month 3 of the CPS surveys.

Figure 8: Occupation Switching Rate by Age



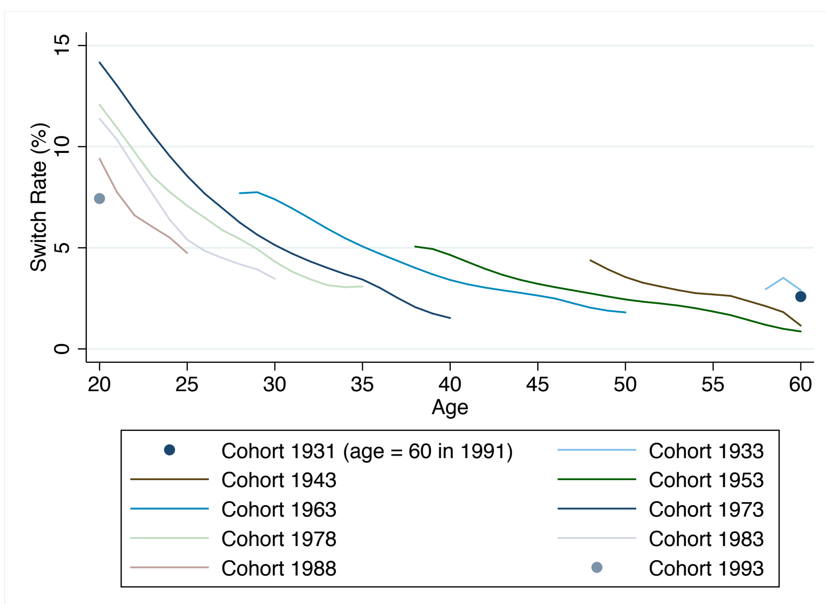
Notes: Author's calculation using SIPP. The occupation code used in constructing occupational switching rate is: Managerial and Professional, Technical Sales and Admin Support, Service Occupations, Farming Forestry an Fishing, Precision Production Craft and Repair, Operators Fabricators and Laborers

Figure 9: Model Time Line



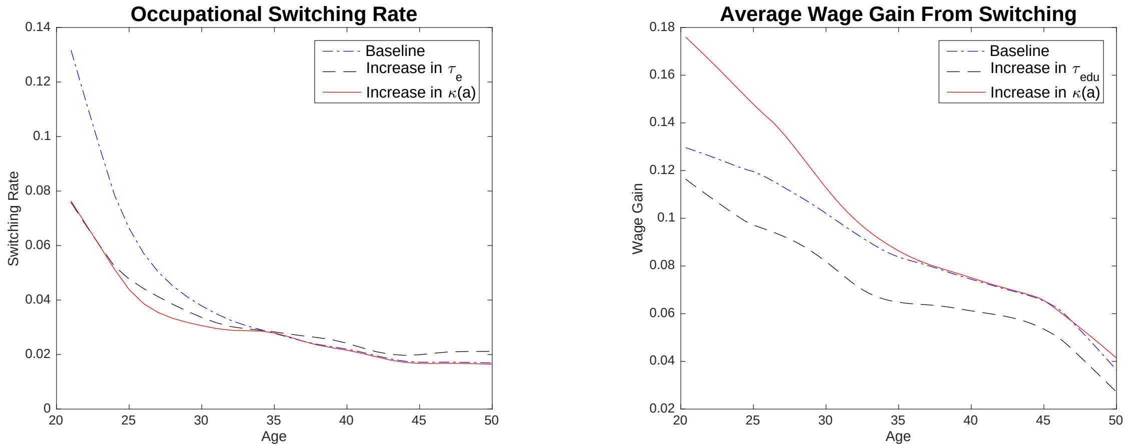
Notes: This figure illustrates typical model agents' time line between time t and time $t + 1$. x denotes agents' state when enter period t, which includes: occupation o, mean of beliefs about each occupation m, the number of times agents have worked at each occupation n; and agents' age a. ζ denotes agents' preference shock for each of the occupation, and j denotes agents occupation choice to work at for period t. Agents are paid at wage w of occupation j, and will pay switching costs κ if they switch occupation between t and $t + 1$.

Figure 10: Occupation Switching Rate by Age (Pseudo Cohort)



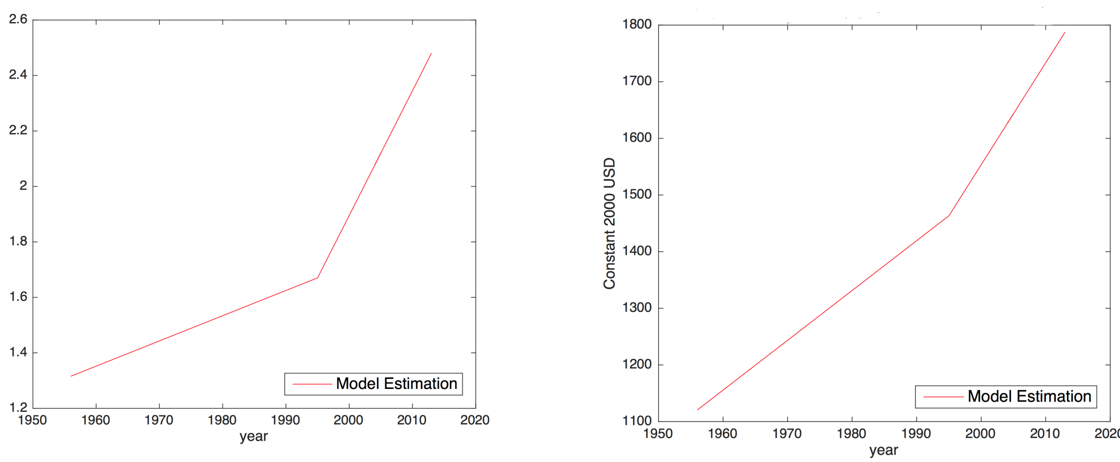
Notes: Author's calculation using SIPP. This plot is smoothed by a locally weighted regression method. The occupation code used in constructing occupational switching rate is: Managerial and Professional, Technical Sales and Admin Support, Service Occupations, Farming Forestry an Fishing, Precision Production Craft and Repair, Operators Fabricators and Laborers.

Figure 11: Identification Illustration



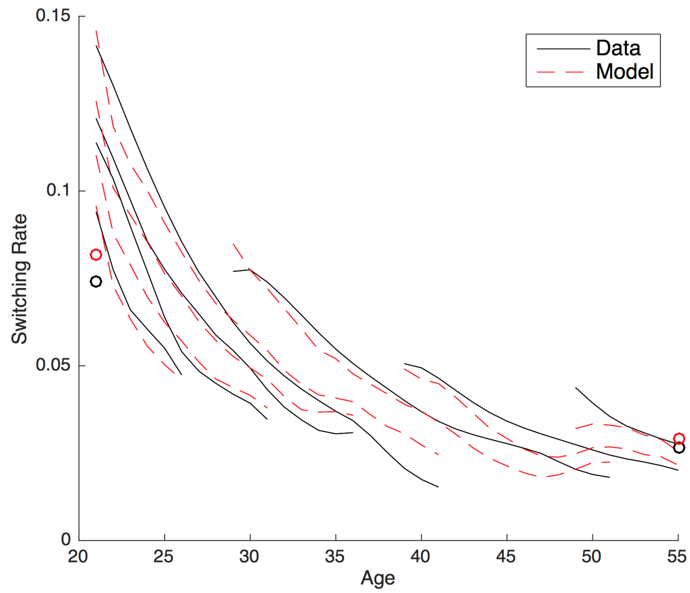
Notes: The left panel shows the effect of information precision and switching costs on occupational mobility by each age group. The right panel shows the effect of information precision and switching costs on wage gain by each age group. For both panels, the black dashline shows the baseline results using calibrated parameters matching cross sectional data in 1993. The blue dashline and red solid line are showing the effect of increasing precision and increasing switching costs, respectively.

Figure 12: Growth Path of Information Precision and Switching Costs



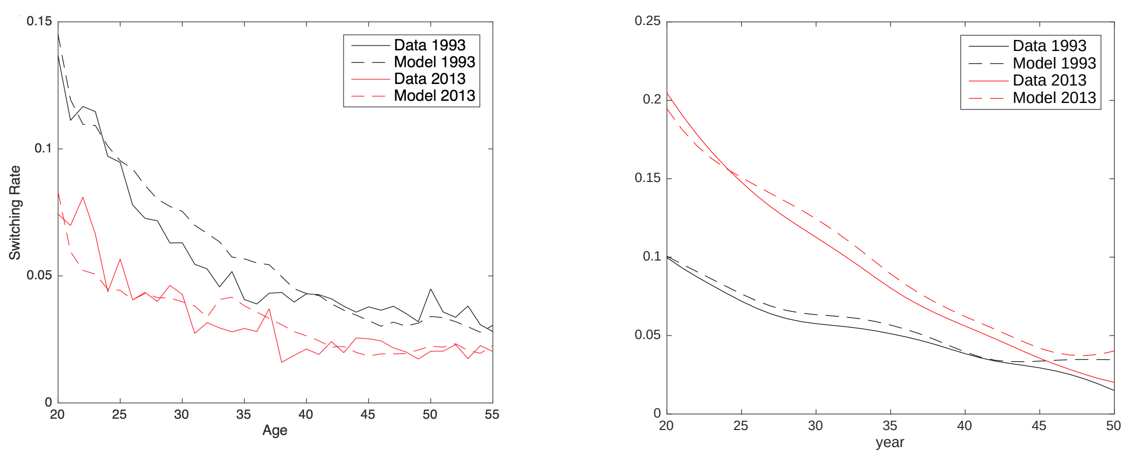
Notes: The left panel shows the calibrated growth path of information precision. The path is calibrated to the synthetic cohort data on occupational switching rate and wage gain using SIPP, and the trend is restricted to piecewise linear. The right panel shows the calibrated growth path of occupational switching costs. The calibration is using the same data and trend as the left panel.

Figure 13: Occupation Switching Rate by Pseudo Cohorts: Data and Simulation



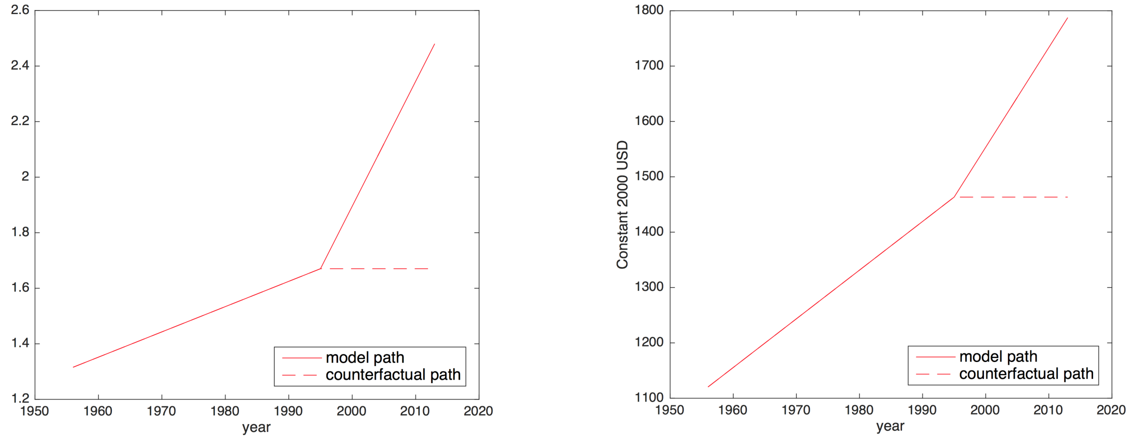
Notes: This figures shows how the simulated economy matches the data. The solid line shows the pseudo cohort occupational switching rate using SIPP as shown in Figure 10. The dash line shows the simulated pseudo cohort switching rate using calibrate parameters.

Figure 14: Cross Sectional Occupation Switching Rates and Wage Gains: Data and Simulation



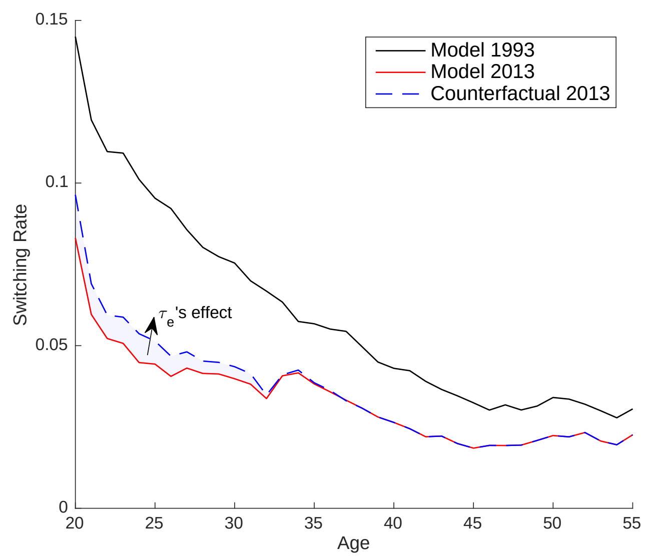
Notes: This figures shows how the simulated economy matches the data. On the left panel, the solid lines show the cross sectional occupational switching rate using SIPP in 1993 and 2013. The dash line shows the simulated cross sectional switching rate, using the simulated pseudo cohort data and assembling the cross sectional economy with the distribution of age in 1993 and 2013 in SIPP. On the right panel, the solid lines show the log wage change for each age group in the cross-sectional data in 1993 and 2013, while the dash lines show the simulated wage change from switching occupations.

Figure 15: Counter-factual Growth Path of Information Precision and Switching Costs



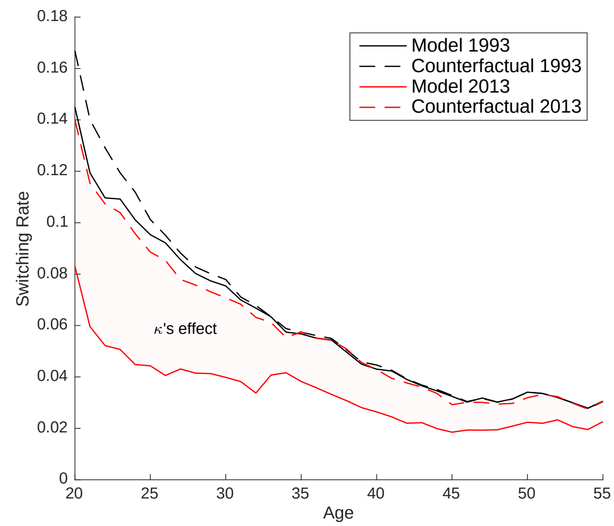
Notes: The left panel shows the calibrated growth path of information precision (solid line), and the counterfactual path (dash line). The path is calibrated to the synthetic cohort data on occupational switching rate and wage gain using SIPP, and the trend is restricted to piecewise linear. The right panel shows the calibrated growth path of occupational switching costs (solid line), and the counterfactual path (dash line). The calibration is using the same data and trend as the left panel.

Figure 16: Occupation Switching Rates by Age (Information Effect)



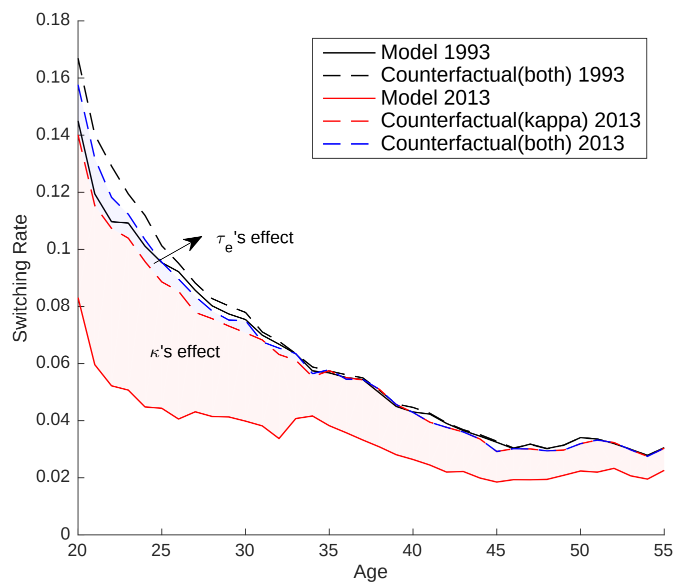
Notes: This figures shows the effect of changes in information precision on occupational switching rates. The solid red and black lines show the cross sectional occupational switching rate using simulated data in 1993 and 2013 respectively, as shown in Figure 14. The dash line shows the counterfactual switching rate in 2013, and the shaded blue area indicate the effect from changes in information precision.

Figure 17: Occupation Switching Rates by Age (Switching Costs Effect)



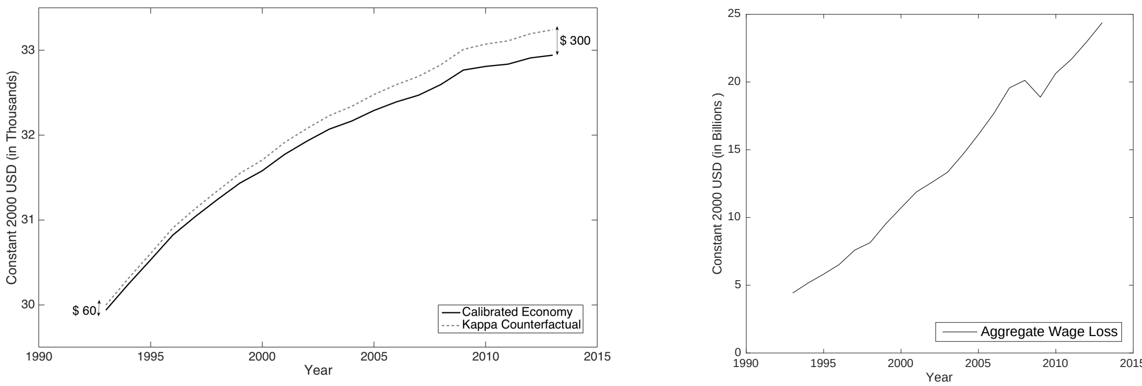
Notes: This figures shows the effect of changes in information precision on occupational switching rates. The solid red and black lines show the cross sectional occupational switching rate using simulated data in 1993 and 2013 respectively, as shown in Figure 14. The dash red and black lines show the counterfactual switching rate in 1993 and 2013 respectively, and the shaded red area indicate the effect from changes in switching costs.

Figure 18: Occupation Switching Rates by Age (Both Factors Effect)



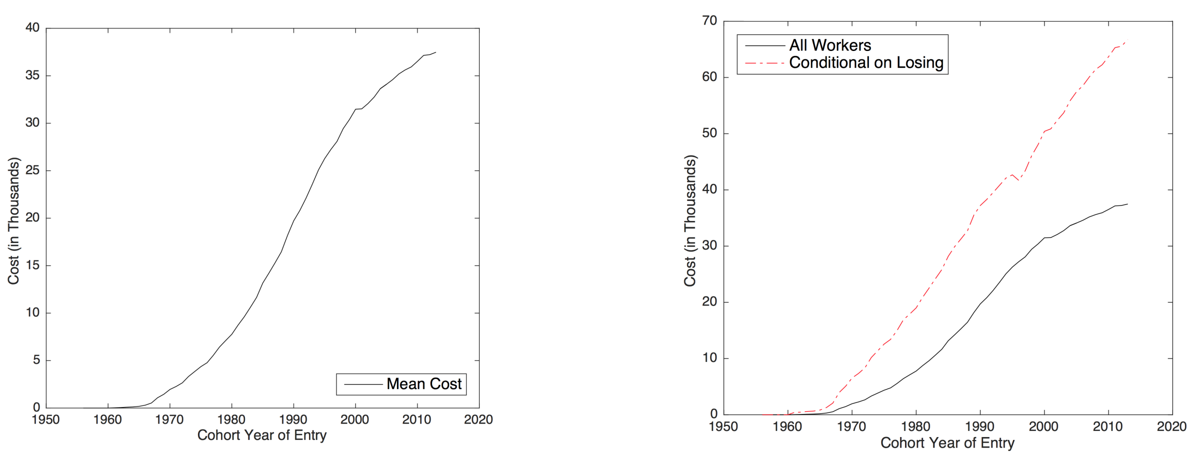
Notes: This figures combines the effect of Figure 17 and Figure 16, and shows the counterfactual occupational switching rate when both information precision and switching costs increase.

Figure 19: Mean Annual Wage Difference and Aggregate Wage Loss from High Switching Costs



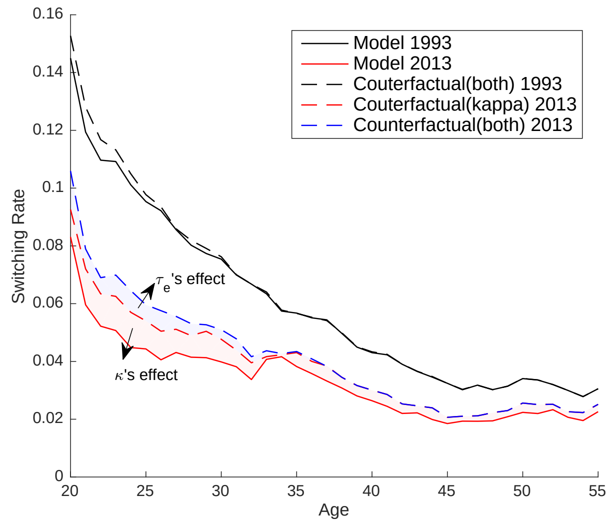
Notes: The left panel shows the mean annual wage for the calibrated economy compared with the counterfactual when switching costs were held at 1995 level. The right panel shows the aggregate effect of this counterfactual exercise.

Figure 20: Lifetime Welfare Cost (Mean) by Cohort



Notes: This figure illustrates the lifetime welfare costs by cohort due to the increase of switching costs. The left panel shows the compensating value by year of entry, averaged over all agents in the economy. The right panel shows the average compensating value for all workers (solid black line, same as the left panel), and for workers who are losing (red dash line).

Figure 21: The Increasing Initial Licensing Costs Effects



Notes: This figures shows the combined effect of changes in information precision and licensing costs on occupational switching rates. The solid red and black lines show the cross sectional occupational switching rate using simulated data in 1993 and 2013 respectively, as shown in Figure 14. The dash red and black lines show the counterfactual switching rate in 2013 due to increased licensing costs, and the blue dash line shows the counterfactual switching rate in 2013 due to licensing and precision.

Table 1: Changes in Transition Matrices

	occ1	occ2	occ3	occ4	occ5	occ6
occ1	0.0644	-0.0430	-0.0049	-0.0015	-0.0080	-0.0070
occ2	-0.0290	0.0669	-0.0094	-0.0008	-0.0100	-0.0178
occ3	-0.0202	-0.0431	0.1118	-0.0025	-0.0133	-0.0327
occ4	0.0071	-0.0154	-0.0243	0.0756	-0.0146	-0.0285
occ5	-0.0248	-0.0476	-0.0114	-0.0044	0.1384	-0.0502
occ6	-0.0076	-0.0222	-0.0049	-0.0018	-0.0167	0.0532

Notes: Author's calculation using SIPP data. The table shows the differences in occupational transition matrices from 1992-1993 to 2012-2013. A positive entry shows that the type of transition is more likely to happen in later time period than earlier years, while a negative entry shows the opposite. The occupational switching rate reflects a four months switching rate. Each entry in the table shows the differences of the transition probability across the 20 years period. Every row of the table adds up to 0. The occupation groups are: occ1: Managerial and Professional occ2: Technical Sales and Admin Support occ3: Service Occupations occ4: Farming Forestry an Fishing occ5: Precision Production Craft and Repair occ6: Operators Fabricators and Laborers

Table 2: Calibrated Parameters

κ_1	κ_2	σ_ν	σ_0	σ_1	σ_2
0.007657	0.000003	3.286007	1.572388	0.022078	0.019409
ψ_0	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5
6.209692	0.023704	-.000141	0.006962	-.000062	-.000022

Notes: This table shows the calibrated parameters. The targeted moments are occupational switching rates for all pseudo cohorts as shown in Figure 10 and the mean income gain from switching.

Table 3: Calibration Results and Counter-factuals

		Data	Model	Counterfactual		
				$\tau_{\mathbf{e}}$	κ	$\tau_{\mathbf{e}}, \kappa$
Switching Rate	1993	5.65%	6.11%	6.11%	6.41%	6.41%
	2013	3.24%	3.29%	3.5%	5.62%	5.85%
				(7.6%)	(71.8%)	(80.2%)
Mean Income	1993	$2498	$2495			
	2013	$2676	$2745	$2743	$2770	$2765
Mean Annual Income		$31,098	$31,871	$31,858	$32,042	$32,018
(Averaged over 1993-2013)				(-0.04%)	(0.53%)	(0.46%)
Lifetime Income	1993		$1.177M	$1.177M	$1.182M	$1.182M
	2003		$1.207M	$1.205M	$1.216M	$1.214M
	2013		$1.224M	$1.223M	$1.234M	$1.233M

Notes: Income is measured in constant 2000 USD. Mean Income is the mean of one month's income. The numbers in brackets represent the proportion of total decline of occupational switching rate, which can be attributed to the following factors: information precision, switching costs, and both.

Table 4: Occupation Licensing Requirement Changes

Occupation	Education (yrs)		Initial Cost		Renewal Cost	
	'95	'13	'95	%Δ ('13)	'95	%Δ ('13)
Engineer	3.7	4.0	$124	55%	$46	101%
Land Surveyor	0.8	4.1	$82	42%	$86	24%
Massage Therapist	0.0	0.0	$89	67%	$42	138%
Psychologist	5.8	6.0	$263	33%	$169	56%
Nurse	2.0	2.0	$36	124%	$26	142%
Teacher	2.3	3.7	$19	177%	$16	188%
Veterinarian	6.0	6.0	$23	512%	$23	468%
Total (Mean)	3.22	4.9	$101	116%	$83	106%

Notes: Author's calculation using the OLLRP. The value shows the average level of requirements cross 30 states in the US. Years of Education: 2 is High School, 4 is Assoc., 6 is Bachelor, 8 is Post-Grad

Appendix

A Universally Licensed Occupations

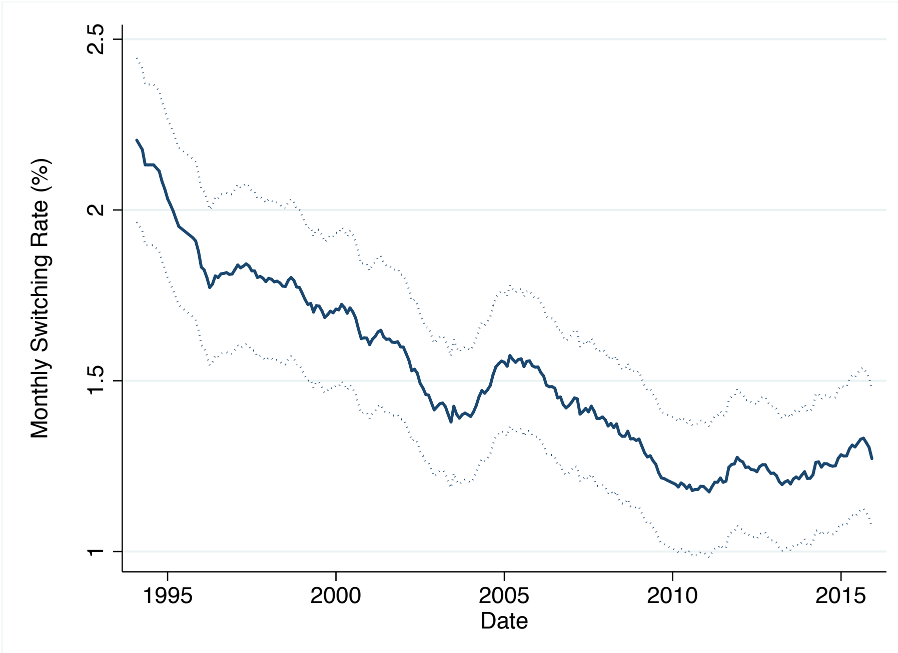
The following occupations are universally licensed in the U.S. (licensed in all 50 states and the District of Columbia). There are many occupations that are partially licensed – licensed in some states but not others. For example, security guards are licensed in 37 states, while bartenders are licensed in 13 states. Note that our main analysis uses agent-specific licensing data that do not rely on knowing these universally licensed occupations.

- Accountant/auditor; Architect (except landscape or naval); Barber; Bus driver (municipal); Chiropractor; Dental hygienist Cosmetologist; Dentist; Emergency medical technician; Engineer; Funeral director; Hearing aid dispenser; Insurance agent; Land surveyor; Insurance adjusters; Lawyer; Practical/vocational nurse; Medical and health service manager; Mortgage loan originator; Registered nurse; Nursing assistant; Occupational therapist; Occupational therapy assistant; Optometrist;Osteopath; Pesticide applicator; Pharmacist; Physical therapist; Physical therapy assistant; Physician assistant; Physician/Surgeon; Podiatrist; Psychologist; Real estate agent; Real estate broker; Real estate appraiser/assesor; School bus driver; School counselor; Securities; commodities and financial service agent; Social worker; Speech language pathologist; Truck driver; Veterinarian; Veterinarian technician/assistant; Teachers.

B CPS Sample Selection

The Current Population Survey (CPS) is a monthly survey of about 50,000 households, which has been conducted by the Bureau of the Census for the Bureau of Labor Statistics. The CPS sample selection in this paper closely follows Moscarini and Vella (2008). We focus on workers who are in their first four months of the sample, and i study their occupation changes between month two and month three. we restrict the sample to male workers who are 20 to 60 years old, and working in both month two and month three. We cleaned the suspicious occupation switches using the ANY3 and FLAG filter as introduced in Moscarini and Vella (2008). The decline of occupation switching rate using the 1990 census occupation classification is significant as it is shown in the main text. The result for more coarsely defined (the six groups are introduced in the main text of the paper) occupation group's monthly

Figure B.1: Monthly Occupation Switching Rate (6 Occupations)



switching rate is shown in Figure B.1. It is clear that the magnitude of the switching rate is smaller when using a coarsely defined groups of occupations, however, the declining pattern remains.

The occupation switching rate pattern holds when the sample selection includes both male and female workers. Including both genders in the sample, and decomposing the demographic effects as done in the paper, the decline remains. The result for monthly occupation switching rate for both male and female workers can be seen in Figure B.2 and the decomposition is shown in Figure B.3.

Lastly, in Figure B.4 we compare the total occupation switching rate versus the job switching rate. The top solid line represents any type of job switching (occupation switching, employer switching, or both). The bottom dashed line shows the occupation switching rate as shown in Figure B.2. The occupation switching rate time series mimics the series for any type of job switching, and can account for more than 70% of the total switching throughout the past 20 years. This provide confidence that occupation switching accounts for the majority of job switching, and thus the story of decreasing job switching cannot be purely an employer switching story. The bottom line is that while the employer switching rate has also declined over this period and is another important area of research worth exploring, this does not reduce the importance of the occupational switching rate decline. Both types of switching

Figure B.2: Monthly Occupation Switching Rate (Both Genders)

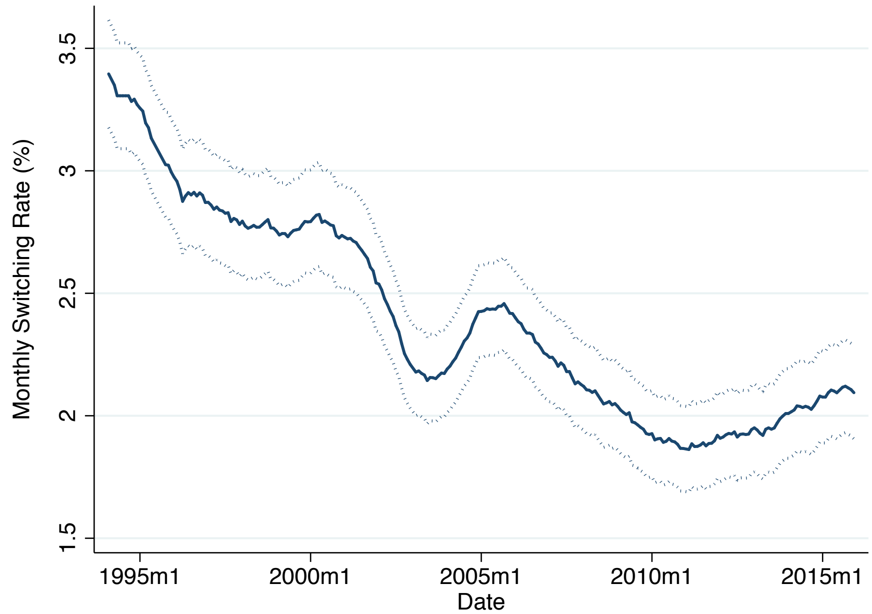


Figure B.3: Decomposition of Occupation Switching Rate (Both Genders)

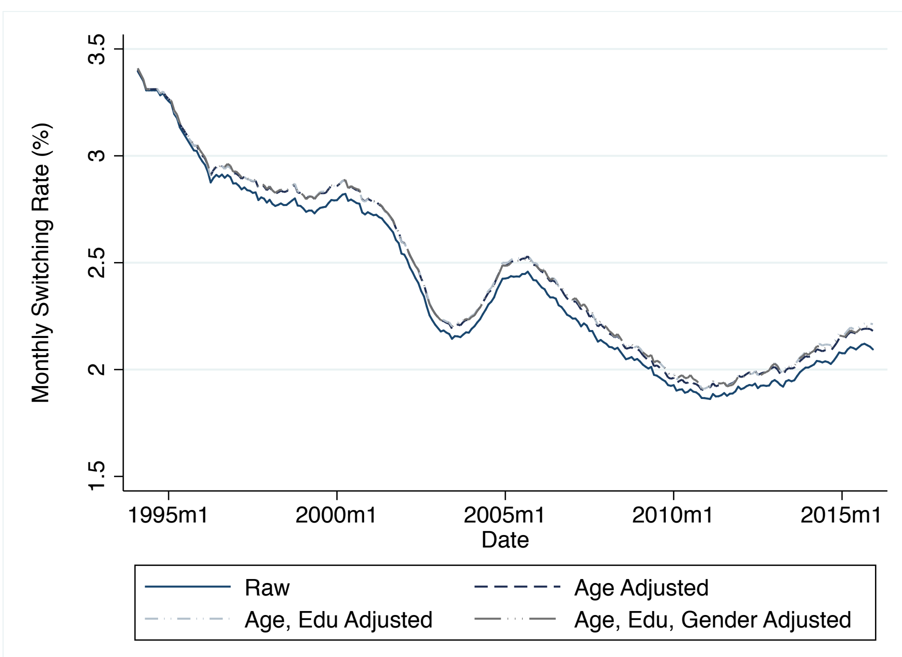
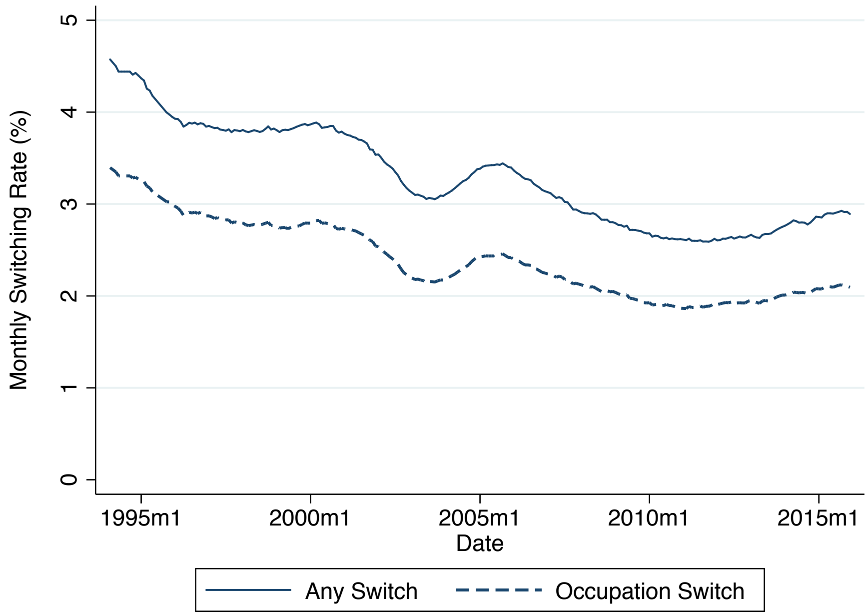


Figure B.4: Job Switch and Occupation Switch



are worthy topics for research and increased attention.

C Identification

This is an simple extension of the example of identification presented in the paper. Here we relax the learning assumption so that it is closer to the set up in the full model. Workers learn about their occupation match quality only after working at that occupation. Their knowledge about other occupations remains unchanged. Under this slightly modified setting, to examine the average wage gain associated with switching, one is interested in the following[36]:

[36] Here we present the case when agents firstly choose occupation b, then switch to a in the second period. This represents the average switch gain, since all the distributions are symmetric and people who switch from a to b are facing the same problem.

$$
\begin{aligned}
&\mathbb{E}\Big[\ \nu^a - \nu^b\ \Big|\ \mathbb{E}(w_1^a < w_1^b),\ \mathbb{E}(w_2^a > w_2^b)\Big] \\
=&\mathbb{E}\Big[\ \nu^a - \nu^b\ \Big|\ e^a < e^b,\ \frac{\tau_e^2}{\tau_e^2 + 1/\sigma_\nu^2} e^a - \kappa \geq \nu^b\Big] \\
=&\mathbb{E}\Big[\ \nu^a - \nu^b\ \Big|\ \nu^a - \nu^b < \eta^b - \eta^a \ \&\ \frac{\tau_e^2}{\tau_e^2 + 1/\sigma_\nu^2}\nu^a - \nu^b \geq \kappa - \frac{\tau_e^2}{\tau_e^2 + 1/\sigma_\nu^2}\eta^a\Big]
\end{aligned}
$$

In the first line, the subscripts 1 and 2 denote the time periods. From the third line of the expression it is clear that when κ increases, the conditional expectation also increases, so the mean of switcher's wage gain increases with the switching costs conditional on switching. However, the effect of increases in information precision τ_e is much less clear. The switching gain can be written as follows:

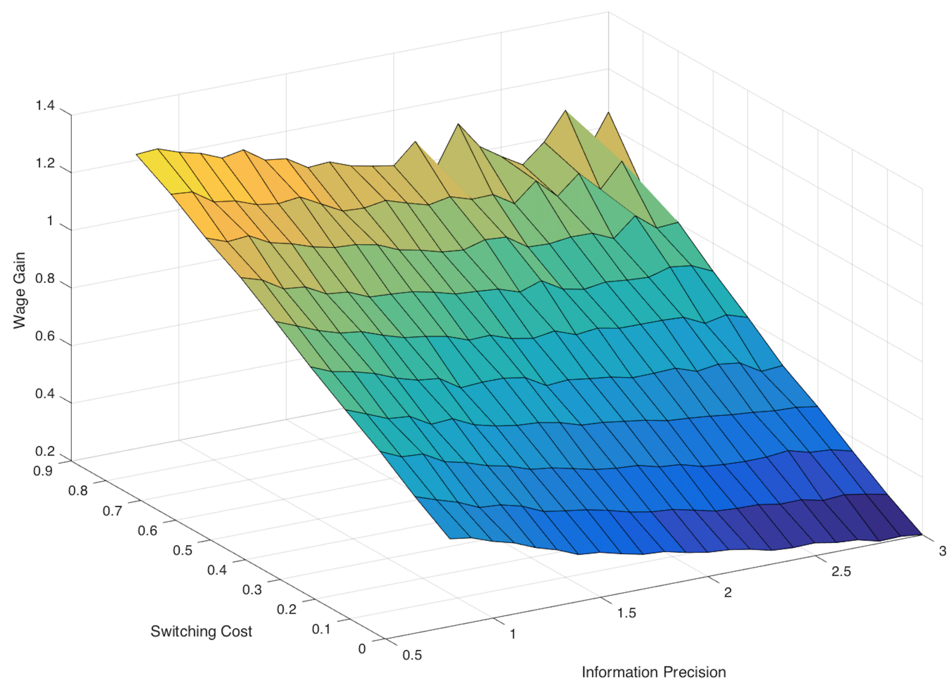
$$
\begin{aligned}
&\frac{\partial \mathbb{E}\Big[\ \nu^a - \nu^b\ \Big|\ \nu^a - \nu^b < \eta^b - \eta^a \ \&\ \frac{\tau_e^2}{\tau_e^2+1/\sigma_\nu^2}\nu^a - \nu^b \geq \kappa - \frac{\tau_e^2}{\tau_e^2+1/\sigma_\nu^2}\eta^a\Big]}{\partial \tau_e} \qquad \eta^a, \eta^b \sim \mathbb{N}(0, \frac{1}{\tau_e}) \\
=&\frac{\partial \frac{\tau_e^2}{4\pi^2\sigma_\nu^2} \int\int\int\int_{\frac{\tau_e^2+1/\sigma_\nu^2}{\tau_e^2}(\nu^b+\kappa)-\eta^a}^{\eta^b-\eta^a+\nu^b} (\nu^a - \nu^b) e^{-\frac{\nu_a^2}{2\sigma_\nu^2}} d\nu^a e^{-\frac{\nu_b^2}{2\sigma_\nu^2}} d\nu^b e^{-\frac{\eta_a^2}{2(1/\tau_e)^2}} d\eta^a e^{-\frac{\eta_b^2}{2(1/\tau_e)^2}} d\eta^b}{\partial \tau_e}
\end{aligned}
$$

It is difficult to sign this analytical expression even in the simplified setting, but one can check the relationship between the conditional expectation and the information precision easily using numerical methods. As shown in Figure C.1, the value of the mean of the wage gain conditional on switching is clearly increasing in switching costs, and decreasing in information[37].

D Additional Results

[37] In the numerical example, we normalize $\sigma_\nu = 1$. We allow $1/\tau_e$ to vary from 0.33 to 1.25 (so τ_e is ranging from 0.8 to 3), so the educational signal is mostly more precise than the information in the population distribution. We let κ vary from 0 to 1, so the switching cost is comparable to the wage level. When both κ and τ_e are big there are very few switchers (high cost, precise information), so the surface plot has jumps and is not as smooth as other parts.

Figure C.1: Occupation Switching Wage Gain: Numerical Example



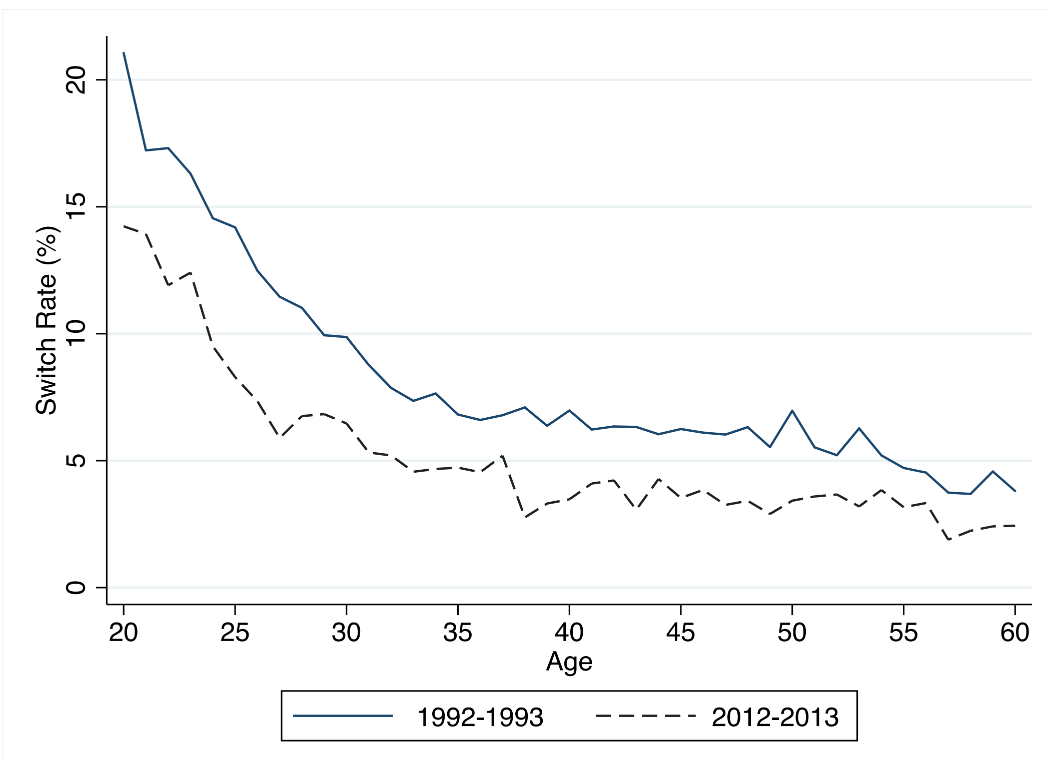


Figure C.2

Table D.1: Changes in Transition Matrices

	occ1	occ2	occ3	occ4	occ5	occ6	occ7	occ8	occ9	occ10	occ11	occ12	occ13	occ14	occ15	occ16	occ17
occ1	0.0281	-0.0011	-0.0054	0.0009	-0.0063	-0.0040	-0.0002	-0.0004	-0.0025	-0.0004	-0.0005	-0.0022	-0.0014	0.0002	-0.0009	-0.0012	-0.0027
occ2	-0.0061	0.0383	-0.0041	-0.0022	-0.0087	-0.0119	-0.0004	0.0006	-0.0019	-0.0001	0.0001	-0.0005	-0.0010	0.0000	-0.0011	-0.0011	0.0000
occ3	-0.0057	-0.0019	0.0222	-0.0014	-0.0056	-0.0038	-0.0002	0.0004	-0.0004	-0.0004	-0.0003	-0.0003	-0.0006	0.0001	-0.0005	-0.0012	-0.0007
occ4	0.0006	-0.0002	-0.0050	0.0297	-0.0033	-0.0064	-0.0008	0.0000	-0.0037	-0.0002	0.0000	-0.0009	-0.0021	0.0000	-0.0014	-0.0041	-0.0021
occ5	-0.0086	-0.0022	-0.0051	-0.0013	0.0418	-0.0085	-0.0009	0.0009	-0.0023	0.0000	0.0000	-0.0013	-0.0020	-0.0001	-0.0015	-0.0030	-0.0056
occ6	-0.0038	-0.0022	-0.0025	-0.0017	-0.0058	0.0224	-0.0006	-0.0006	-0.0013	-0.0002	-0.0003	-0.0004	-0.0002	0.0003	-0.0003	-0.0021	-0.0008
occ7	-0.0039	-0.0010	-0.0028	-0.0020	-0.0100	-0.0044	0.0623	-0.0018	-0.0223	-0.0005	-0.0009	-0.0026	-0.0005	0.0000	-0.0006	-0.0047	-0.0041
occ8	-0.0034	-0.0011	-0.0022	0.0011	-0.0041	-0.0058	0.0001	0.0406	-0.0041	0.0000	-0.0003	-0.0031	-0.0016	0.0000	-0.0024	-0.0056	-0.0081
occ9	-0.0046	-0.0009	-0.0003	-0.0019	-0.0069	-0.0091	-0.0019	-0.0013	0.0402	-0.0001	-0.0006	0.0001	-0.0020	0.0001	-0.0006	-0.0070	-0.0032
occ10	0.0087	-0.0016	0.0095	-0.0013	-0.0105	0.0119	-0.0016	-0.0024	-0.0093	0.0217	-0.0061	0.0017	-0.0066	0.0000	-0.0023	-0.0051	-0.0067
occ11	-0.0047	0.0000	-0.0048	-0.0006	-0.0121	-0.0028	-0.0009	-0.0016	-0.0085	-0.0059	0.0659	-0.0038	-0.0019	0.0000	-0.0018	-0.0051	-0.0115
occ12	-0.0061	-0.0018	0.0004	-0.0018	-0.0055	-0.0014	0.0000	-0.0010	-0.0002	-0.0002	-0.0009	0.0297	-0.0016	0.0008	-0.0016	-0.0040	-0.0046
occ13	-0.0047	-0.0006	-0.0025	-0.0028	-0.0047	-0.0024	-0.0003	-0.0006	-0.0006	-0.0013	-0.0015	-0.0051	0.0457	0.0000	-0.0024	-0.0091	-0.0073
occ14	-0.0043	0.0000	0.0000	-0.0081	-0.0183	0.0044	0.0000	-0.0055	0.0000	0.0000	0.0000	-0.0017	0.0088	0.0426	-0.0058	-0.0075	-0.0046
occ15	-0.0042	-0.0010	0.0001	-0.0013	-0.0036	-0.0023	-0.0006	-0.0014	-0.0010	-0.0005	-0.0001	-0.0056	-0.0033	0.0000	0.0380	-0.0091	-0.0041
occ16	-0.0017	-0.0009	-0.0020	-0.0012	-0.0046	-0.0057	-0.0004	-0.0003	-0.0016	-0.0005	-0.0004	-0.0027	-0.0019	0.0003	0.0009	0.0298	-0.0071
occ17	-0.0021	-0.0009	0.0000	-0.0006	-0.0067	-0.0034	-0.0003	-0.0016	-0.0007	-0.0010	0.0000	-0.0044	-0.0055	-0.0006	-0.0027	-0.0072	0.0376

Notes: Author's calculation using SIPP data. The table shows the differences in occupational transition matrices from 1992-1993 to 2012-2013. A positive entry shows that the type of transition is more likely to happen in later time period than earlier years, while a negative entry shows the opposite. The occupational switching rate reflects a four months switching rate. Each entry in the table shows the differences of the transition probability across the 20 years period. Every row of the table adds up to 0. The occupation groups are: OCC1: Executive, Administrative, and Managerial Occupations OCC2: Management Related Occupations OCC3: Professional Specialty Occupations OCC4: Technicians and Related Support Occupations OCC5: Sales Occupations OCC6: Administrative Support Occupations OCC7: Housekeeping and Cleaning Occupations OCC8: Protective Servce Occupations OCC9: Other Service Occupations OCC10: Farm Operators and Managers OCC11: Other Agricultural and Related Occupations OCC12: Mechanics and Repairers OCC13: Construction Trades OCC14: Extractive Occupations OCC15: Precision Production Occupations OCC16: Machine Operators, Assemblers, and Inspectors OCC17: Transportation and Material Moving Occupations